FCTUC FACULDADE DE CIÊNCIAS E TECNOLOGIA UNIVERSIDADE DE COIMBRA

OPTIMUM DESIGN OF AVIATION NETWORKS

THE CASES OF AIRPORT CONGESTION AND LOW DEMAND

Doctoral thesis

Thesis submitted to the Faculty of Sciences and Technology of the University of Coimbra in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the field of Transport Systems.

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Coimbra. August, 2012

In memory of the one that has guided me since the beginning,

António da Rocha Pita

'I think that everything is possible as long as you put your mind to it and you put the work and time into it.'

Financial support

This research work was conducted under the MIT-Portugal Program and financed by "Fundação para a Ciência e a Tecnologia" (FCT, Portugal) through the Ph.D. grant with reference SFRH / BD / 43060 / 2008, and was co-financed by the European Social Fund (ESF) within the "Programa Operacional Potencial Humano" (POPH). The POPH research program is integrated in the "National Strategic Reference Framework 2007-2013 - Tipologia 4.1 – Formação Avançada" (QREN 2007-2013).

Acknowledgements

My deepest gratitude goes to Professor Pais Antunes for having challenged me to do this PhD and to have provided me with his permanent support without which this thesis would have been almost impossible to complete. Since the beginning we have embraced this journey together facing new challenges posed by the aviation sector. His permanent guidance and belief in my capacity to perform this work is something that I'm truly grateful for. Last but not the least he has been a great role model in terms of optimism, objectivity, and work ethics.

I sincerely thank Professor Cynthia Barnhart for her unique insights and valuable remarks. I will always remember the meetings at MIT where I have benefited from her vast knowledge on operations research and aviation. Her kind words and constant incentive were precious elements for my daily motivation during the year spent at MIT.

I would like to acknowledge the kind support from Professors Amedeo Odoni and Nicole Adler. I see both as mentors and friends. Professor Odoni words of confidence and unmatchable experience have contributed decisively to the outcome of this thesis. Professor Adler has guided me to a new level of assertiveness and professionalism. Working with her is an amazing experience both professional and personally.

My thankfulness goes also to Fundação para a Ciência e Tecnologia (FCT) and MIT-Portugal Program for their financial support. It has allowed me to continue my studies both in Portugal and at MIT. Moreover, it has been essential for me to be able to present my work in major conferences all around the world. A special reference must be made for the University of Coimbra, especially the Faculty of Sciences and Technology, for all the institutional and logistics support.

I want to express my gratitude to TAP and SATA for having provided me with very useful data for the case studies, and their respective CEOs, Fernando Pinto and António Menezes, for their openness to collaboration. From TAP, I want to acknowledge particularly José Adolfo, Maria João Dias, and Alexandre Coutinho for their insightful comments about the TAP network, and, from SATA, Ana Azevedo and Bruno Gomes for their remarks about the SATA network.

I want to acknowledge all my colleagues and friends at the Department of Civil Engineering. During the last eleven years we shared dreams and ambitious, we smiled together and we have supported each other. Thank you to my officemates Susana and João, who have already left the office, Mark, with his permanent good spirit, and the new "roomies" Ashenafi, Joana, and Rodrigo. A special mention must be made to Bruno and Nuno, for their leadership role, and to Diana, for being a companion since day one.

To my *MIT crew*, thank you very much for helping me spending such good times in Cambridge. The year at MIT was amazing both academically and personally thanks to all of you. To my housemates Miguel, Ana Laura, Vishal, and Sérgio, all the credits for making me laugh at home and for the great dinners and evenings together. To Alda, Carlos, David, Daniela, and Eunice, thank you for your friendship and support. To my Greek friends, thank you for amazing soccer games, even with below zero temperatures. To Chris Grillo, who has made me look like an expert on baseball and American football. To my officemates Carlos, Li, Marty, and Swapnil, thank you for your generosity and friendship. Finally, to my AirNets friends, Vikrant, Nikolas, Alda, and Miguel, thank you for the amazing conferences and seminars that we have attend together.

I will always be indebted to my best friend Hugo Repolho, with whom I have accomplished so many dreams. He is and will always be much more than a friend. But I am very fortunate to have a great group of friends, particularly my JSC, 968 and Lisbon friends, which are always supporting me. A special allusion to the great friends I made during my academic activities, especially my 2005 and 2007 teams, and all the friends I have throughout the country. I cannot forget my swimming coach, Paulo Tejo. He and my team at AAC were responsible for shaping the person I am today.

I cannot express in words the gratitude I feel for the unquestionable support and love that my parents have given to me. I can close my eyes and remember our long and exciting conversations. I am most of all a product of their education. My brother Francisco is a true companion. In our differences we can get the best of each other. I want to express my thankfulness to my family for their permanent encouragement. We might not be a large family but we are beyond any doubt a great family.

Finally, to my better half Liliana, the most amazing person I have ever met, my most deeply thank you. In this journey you have been the utmost and true support. Your love and passion have given me the strength and courage to embrace this day by day journey. But remember that this is just a chapter about to be closed while an entire life together is about to be open.

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Abstract

Air transportation liberalization led to significant changes on aviation because of a substantial increase in air transportation demand. The airline industry has diversified its business models, adopting a hub-and-spoke network structure and creating low cost carriers. Consequently, airfares dropped and competition and flight frequency increased for the main markets. But it has also contributed for increasing congestion at airports and to the establishment of subsidy schemes to serve sparsely populated regions with implications for airlines and passengers. This thesis is concerned with the development of specific tools to deal with these two types of air transportation networks. The thesis extends the existing work in network design formulation to the situation of both congested and low demand networks.

Aviation network design models determine the flight schedule and fleet assignment for a given network. Typically, they are developed by airlines as a core part of the airline planning process. In this thesis, these models are extended to encompass other perspectives. Three main perspectives are dealt with in this thesis: airline, aviation authority, and government. The optimization models proposed are linear and mixed-integer with the objective of maximizing profits or minimizing costs.

Networks operated under congestion are becoming more frequent as airport capacity is incapable to cope with the increasing demand for air transportation. This phenomenon is responsible for very large costs for airline and passengers. Therefore, it is necessary to mitigate delays without compromising airline profitability, passengers' connectivity and service frequency. Three optimization models were developed in the thesis to study delay impacts in the perspective of governments, airlines, and aviation authorities.

After liberalization, both the US and the EU launched subsidy schemes to prevent sparsely populated and remote regions from becoming underserved with respect to air transportation. In this case, schedule services without subsidies would not be viable. Governments set a minimum level of service to be satisfied by the operating airline and, at the same, give public subsidies for its operation. In this thesis, two decision approaches are developed to help governments setting the level of service required to be satisfied by the airlines. These decision approaches are based on network design optimization models in which all relevant costs and revenues for the government analysis are involved, including airline and airport costs and revenues, and passenger time costs.

Another objective of the thesis was to apply the models to case studies based on real world networks. Indeed, all models were applied to different networks, depending on their objectives, with significant improvements from the current networks. Formulations could cope with the size and complexity of real world networks, as all the applications reached optimal solutions. For congested networks were used the Portuguese air transportation system (Chapter 2), the main European network (Chapter 3), and the TAP network (Chapter 4). For subsidized networks were used the Azores network (Chapter 5) and the Norwegian regional network (Chapter 6). Results show the usefulness of the optimization models as capable tools to help airlines, aviation authorities, and governments in their network design decisions.

Resumo

A liberalização do sistema de transporte aéreo, primeiro nos EUA e depois na Europa, transformou significativamente o sistema existente, com efeito direto no aumento da procura de viagens aéreas. Para este aumento contribuiu também a mudança no modelo de negócio das companhias aéreas, seja pelo aparecimento das companhias *low-cost*, seja pela mudança operacional para um sistema *hub-and-spoke*. Paralelamente, os preços diminuíram, a competição entre companhias aumentou e a frequência de voos cresceu substancialmente nas rotas mais lucrativas. A abertura do mercado teve também algumas consequências que podem ser consideradas negativas, entre as quais, o aumento dos atrasos e congestionamento nos maiores aeroportos e a necessidade de estabelecer esquemas de subsídio para manter as operações aéreas para locais remotos e/ou de fraca procura.

Esta tese aprofunda o trabalho existente na formulação do desenho de redes de transporte aéreo para as situações específicas de redes de transporte aéreo operadas seja com congestionamento, seja com subsídios públicos.

Os modelos de desenho de redes desenvolvidos determinam, para cada situação em análise, o horário e o tipo de avião para cada voo. Estes modelos foram concebidos para serem aplicados por companhias aéreas como parte central do seu planeamento operacional. Nesta tese, contudo, estes modelos são adaptados a outras situações e perspetivas, como sejam, governos e autoridades aeronáuticas. Os modelos de otimização propostos são lineares e inteiros-mistos tendo como objetivo maximizar lucros ou minimizar custos de uma rede de transporte aéreo.

O congestionamento nos maiores aeroportos mundiais tem vindo a crescer à medida que a procura desses aeroportos se aproxima da sua capacidade máxima. Esta situação origina custos muito significativos para as companhias aéreas, para os passageiros e para a economia. Desta forma, é necessário mitigar o efeito dos atrasos sem comprometer a viabilidade económica das companhias aéreas nem o nível de serviço e conectividade dos passageiros. Esta tese estuda os efeitos do congestionamento através de três modelos de otimização desenvolvidos para uma rede em que aeroportos e companhias aéreas são controlados publicamente, para uma rede de aeroportos e companhias que operam e competem num sistema congestionado e para uma companhia aérea que opera em competição.

Durante o processo de liberalização do transporte aéreo foi identificada a necessidade de salvaguardar as regiões (e populações) remotas para as quais a acessibilidade depende da existência de ligações aéreas. Neste caso, os governos podem subsidiar a operação destas rotas, estipulando, para tal, serviços mínimos a serem cumpridos pela companhia aérea. Nesta tese são desenvolvidas ferramentas para apoiar os governos em decisões sobre os requisitos a exigir às companhias aéreas. Estas ferramentas baseiam-se em modelos de otimização do desenho de redes nos quais são tidos em conta os custos e receitas das companhias aéreas, os custos do tempo dos passageiros e os custos e receitas de operação dos aeroportos.

Outro objetivo desta tese é a aplicação dos modelos desenvolvidos a estudos de caso baseados em problemas reais. Efetivamente, todos os modelos foram aplicados a redes de transporte aéreo, dependendo do seu objetivo e contexto. As formulações são capazes de lidar com a dimensão e complexidade das redes existentes, tendo atingido o resultado ótimo em todas as situações. Para as redes com congestionamento as aplicações foram à rede portuguesa de transporte aéreo (Capítulo 2), ao conjunto dos 10 maiores aeroportos e 9 maiores companhias aéreas na Europa (Capítulo 3) e à rede da TAP (Capítulo 4). Para as redes subsidiadas foi usada a rede do Arquipélago dos Açores (Capítulo 5) e a rede regional da Noruega (Capítulo 6). Os resultados obtidos demonstram as potencialidades dos modelos desenvolvidos e a sua utilidade prática para companhias aéreas, governos e autoridades aeronáuticas.

OPTIMUM DESIGN OF AVIATION NETWORKS

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Chapter 1

Introduction

1.1 Background

The liberalization of air transportation in developed economies, particularly North America and Europe, has shifted decisively the mobility of people and goods over the last 30 years. Indeed, the growth in air transportation demand after liberalization has been much higher than before: for the European Union (EU) the annual growth in the number of passengers was around 33 percent after the 1992 liberalization comparing to values in the 1980s of 4 to 6 percent (INTERVISTAS, 2006). Furthermore, as the world becomes more global and the need for transportation and communication increases, the impact of air transportation beyond the industry raises (GOETZ and GRAHAM, 2004). In 2006, the industry had an induced impact on world GDP and employment of over USD 1.1 trillion and 14.7 million, respectively (ATAG, 2008).

For the future, it is expected that liberalization will extend to other parts of the World, especially developing countries. Indeed, according to IATA (2007) only 17 percent of the international traffic is conducted in a deregulated environment and cabotage rights are forbidden for foreign airlines except within the European Union. Despite that, it is forecast that demand for air travel will continue to increase at a fast rate not only in developing regions but also in mature markets (IATA, 2011).

As demand for air transportation, competition between airlines and airports, and airport usage is increasing, it becomes more important to improve the design of air transportation networks in order to cope with the multiple challenges faced by the industry. The development of air transportation also led to diversified airline and airport business models and to changes in the government role.

In a liberalized system, the competition between airlines led to changes in the airline operations: point-to-point to hub-and-spoke network configuration; concentration in the most profitable routes; and an overall yield reduction, although hub premiums may be charged by air carriers in their hubs (PELS, 2008). Another main change in the last 25 years was the emergence of low-cost airlines. It has driven new passengers to the industry, through the launch of new routes, which has made regional/secondary airports appear as competitors for traditional airports. Airports have diversified their revenues, and commercial revenues currently accounting for almost half of total airport revenues (GRAHAM, 2009), while their market power has been reduced considerably as airlines can enter and exit airports much more easily (STARKIE, 2012) and competition from secondary airports has risen. Finally, governments are adopting a more regulatory rather than ownership role, with the privatization of many previously state-owned airlines especially in Europe (ALVES and BARBOT, 2008). The regulatory roles, where governments are a key stakeholder, focus on bilateral agreements for international traffic and on airport ownership and slot allocation definition. All the previous changes combined have enhanced consumer welfare by increasing flight frequency and lowering prices (SCHIPPER et al., 2007).

Despite all gains from liberalization, there are some consequences that might hamper some benefits in the future if not dealt with properly. On the one hand, demand for airport capacity has increased much more than supply leading to severe delays at the main airports that may compromise future growth of air transportation. On the other hand, sparsely populated regions had become underserved without subsidy schemes, as airlines shifted their operations towards more profitable routes.

Congestion and airport delays are a direct, and probably inevitable, effect of the growth in air transportation, as many busy airports lack capacity to accommodate flight demand (NERA, 2004). Airport capacity is, indeed, a serious limitation to the growth in air transportation (DE NEUFVILLE and ODONI, 2003). A comprehensive study by NEXTOR (2010) estimates the cost of delays for the US economy in 2007 to be 32.9 billion USD, of which more than 16 billion USD were direct costs for passengers and 8 billion direct costs to airlines. The delay cost for the airlines can be compared with an overall profit of 5 billion USD for the US domestic carriers in 2007 (ATA, 2008). In Europe, average arrival delay in 2011 was 10.3 minutes comparing to 15 minutes in 2010, which is equivalent to an average of, respectively, 28.6 and 34.7 minutes per delayed flight. Almost half of delay in Europe is reactionary delay that cannot be accommodated by airline schedules (CODA, 2011; CODA, 2012). In the long-term, congestion can be coped with the expansion of existing airports or the construction of new ones. In the short-term, however, it must be handled through a better use of airport capacity, with appropriate demand management measures, and through network design improvements.

The need for subsidizing networks connecting remote or sparsely populated regions was identified during the liberalization process to mitigate the predictable effects of a shift of airline operations to the most profitable routes with an unacceptable reduction of service for low demand regions (SANTANA, 2009). Consequently, both the US and the EU have created similar programs, respectively called Essential Air Service, EAS, and Public Service Obligation, PSO (BRAATHEN, 2011). Within these programs, public authorities award subsidies to airlines for operating those routes as a monopoly while satisfying required levels of service (WILLIAMS, 2005). In Europe, usual PSO requirements are the minimum flight frequency or number of seats per leg, maximum airfares, connectivity requirements, or aircraft requisites. Public authorities in charge of PSO need on the one hand, to: enhance accessibility to remote regions providing them with adequate air services and, on the other hand, to prevent excessive subsidies to the airlines, balancing public and private expenditure for the use of the air transportation network. Thus, the decision approach for setting PSO requirements can be seen as a network design problem for which social welfare considerations need to be taken into account.

1.2 Research objectives

The goal of this thesis is to develop aviation network design models for the cases of airport congestion and low demand. To the best of the author’s knowledge, there is no literature available about optimization models developed and applied to these types of air transport networks. I believe that the one-fits-all approach of the existing network design models may not be sufficient to fully cover particular problems and issues that arise on congested and low demand networks, such as, passenger disruptions or the definition of a minimum level of service.

In this thesis, network design models are dealt with from the airlines, governments, and aviation authorities' perspectives in their operational, political, and administrative decisions, respectively. One main and three specific objectives have been set for congested and low demand networks.

For congested air transportation networks, addressed on Chapters 2 to 4, the main objective is to develop optimization models that include flight and passenger delay considerations to mitigate the impact of congestion in air transportation networks. The specific objectives are as follows:

1. Analyze the impacts of delays for airlines and passengers, particularly for disrupted passengers.
2. Include airline slot constraints in network design models focusing on governments, airlines, and aviation authorities.
3. Analyze the effect of airline competition for airport and airline delays in liberalized air transportation networks.

For low demand air transportation networks, addressed on Chapters 5 and 6, the main objective is to develop decision approaches to define the minimum level of service for subsidized air transportation networks, based on network design optimization models. The specific objectives are as follows:

1. Analyze the usefulness of the decision approach to help government setting efficient level of services to be met by the operating airlines.
2. Estimate passenger demand functions for low demand and subsidized air transportation networks as function of maximum airfares, network configuration, and required level of service.
3. Analyze trade-offs between government, airport, airline and passenger welfare or cost savings from different level of service requirements.

An additional objective of this thesis is to apply the models to real-world networks. These networks were chosen taking into account the specific problem to be addressed, the type of network, and the availability of data. It should be noticed that, despite the effort made to have access to the largest set of real-world information to accurately replicate the existing networks, the applications are hypothetical case studies.

1.3 Outline

The thesis is divided in seven chapters, being Chapters 1 and 7, respectively, the thesis introduction and conclusion. The five main chapters, Chapters 2 to 6, are all written in the format of a scientific paper. Some have already been submitted or accepted for publication, and others are expected to be submitted in the next months. This means that all chapters have an introduction, problem definition, model formulation, and an application. Consequently, the reader can decide to read the thesis in succession or each chapter independently. Inevitably there are some repetitions throughout the document that could not be avoided.

Even though each chapter can be read independently this thesis forms a consistent document and not only a collection of papers. Indeed, all chapters address a different aviation network design problem.

Chapters 2, 3 and 4 are devoted to congested networks, that is, networks that in frequent circumstances operate with delays. Also, the focus is on networks operated using mainly slot-constrained airports. Airport delays that can be mitigated are due to lack or less than optimal usage of airport capacity, or due to airline scheduling options that cannot accommodate expected delays. Three optimization models were developed to address these issues with different perspectives and complexity.

Chapter 2 introduces an optimization model to determine the best possible slot allocation decisions for a publicly-controlled aviation network. The model is aimed at determining the best decisions to be made by the public authority (government or aviation authority on its behalf) with regard to airport slotallocation for a given aviation network and also to the flight schedules of the publicly-controlled airlines. The leg-based demand for flights and the capacity of the airports are assumed to be known. The objective is to minimize the total social costs of satisfying a given leg-based air travel demand. The costs to minimize include flight costs, airport costs, passenger time costs, congestion costs, and spilled passenger costs. The practical usefulness of the model is illustrated with an application to the main aviation network of Portugal.

Chapter 3 presents an optimization model to analyze whether airport capacity and airline slot distribution are capable to accommodate the expected passenger demand with lower costs to the network, including airport delay costs. The approach is set to be use in a liberalized, busy, congested, and slot-constrained air transportation network.

The optimization model developed to cope with the objective, determines the minimum cost network configuration (flight frequency, flight time, seats per leg) taking into account the market power of each airline, passenger demand per flight-leg, and expected values of airport delays. The usefulness of this approach is shown with an application to a network comprising 10 of the largest and most congested airports in Europe.

Chapter 4 introduces an integrated flight scheduling and fleet assignment optimization model that takes aircraft and passenger delay costs explicitly into account. The objective of the model is to maximize the expected profits of an airline that faces a given O/D-based travel demand and operates in congested, slot-constrained airports. Both airline competition and airline cooperation are dealt with in the model, though in a simplified manner. The model was applied to a case study involving the main network of TAP Portugal, which comprises 31 airports and 100 daily flights legs.

Chapters 5 and 6 deal with subsidized air transportation networks. These networks connect sparsely populated regions, which are very often remote regions whose accessibility relies on air transportation. In both chapters, the objective is to develop a decision approach to define Public Service Obligations (PSO) requirements based on network design optimization models. Such an approach may prove valuable to governments responsible for designing public support systems, whose objective is to increase accessibility to sparsely populated regions yet minimize public expenditure over the air transport network.

Chapter 5 proposes a decision approach designed to assist governments (aviation authorities) in the definition of PSO requirements. The approach is based on an integrated flight scheduling and fleet assignment optimization model that minimizes the total social costs of satisfying a given target origin/destination demand. With the outputs of the optimization model the maximum airfares per market as well as the amount of public subsidies necessary to finance the network are computed. The usefulness of the approach is illustrated with an application to the network of Azores, one of the main European networks fully-operated according to the PSO system.

Chapter 6 presents an approach to evaluate the social welfare of an air transportation network run under public support systems. The approach is based on a welfare based integrated flight scheduling and fleet assignment optimization model (WFSFA) that extends the optimization model presented in Chapter 5 mainly by considering airport costs, improving the passenger level of service analysis, and relaxing the hypothesis of a given targeted demand. With the optimization model outputs, a social welfare analysis is done distinguishing between passenger, airline, airport, and government surplus. The usefulness of this approach is shown with an application to the regional Norwegian network, which is the largest in Europe.

Finally, Chapter 7 summarizes the work done within the scope of this thesis as well as its main conclusions.

1.4 Publications

As mentioned before, this thesis is organized on the basis of scientific papers. It is therefore important to refer the publications that are expected to result from the research made during the four years of the doctoral program.

Some of the papers have been submitted to international journals and have been accepted for publication or are under review, and others will be submitted soon.The paper about the research made on integrated flight scheduling and fleet assignment under congestion with the application to the TAP network (Chapter 4) has been accepted for publication in *Transportation Science*. The paper about publicly-owned air transportation networks with the application to the Portuguese network (Chapter 2) has been submitted to the *Journal of Air Transportation Management*. The paper that analyzes whether airport capacity and airline slot distribution are capable to accommodate the expected passenger demand with lower costs to the network, including airport delay costs with an application to the ten airports and 8 largest airlines in Europe (Chapter 3) has not been submitted yet. The papers resulting from the research made about subsidized networks with an application to the Azores network was recently submitted to *Transportation Research Part A: Policy and Practice* (Chapter 5) and the one with an application to the Norwegian regional network will be submitted very shortly to *Transportation Research Part B: Methodological* (Chapter 6).

Beside the publications, the dissemination of the research developed in the doctoral program has been made in several international and national conferences between 2009 and 2012. Indeed, all papers have been presented and discussed previously in one or more conferences. The full list of conferences is the following:

- *13th Air Transport Research Society Conference* (13th ATRS), June 27-30, 2009, Abu Dhabi, United Arab Emirates – Chapter 2;
- *23rd European Conference on Operational Research* (XXIII EURO), July 5-8, 2009, Bonn, Germany – Chapter 2;

- *International Workshop on Advances in Airport, Air Traffic, and Airline Network Design*, April 27, 2010, Lisbon, Portugal – Chapter 4;
- *7th Triennial Symposium on Transportation Analysis* (TRISTAN VII), June 20-25, 2010, Tromso, Norway – Chapter 4;
- *14th Air Transport Research Society Conference* (14th ATRS), July 6-9, 2010, Porto, Portugal – Chapter 4;
- *12th World Conference on Transportation Research* (XII WCTR), July 11-15, 2010, Lisbon, Portugal – Chapter 4;
- *8º Encontro do Grupo de Estudos em Transportes (8º GET)*, January 6-7, 2011, Esmoriz, Portugal – Chapters 3 and 4;
- *15º Congresso da Associação Portuguesa de Investigação Operacional* (IO 2011), April 18-20, 2011, Coimbra, Portugal – Chapters 2, 3 and 4;
- *1st Annual INFORMS Transportation Science and Logistics Society Workshop: Congestion Management of Transportation Systems on the Ground and in the Air* (), June 26-29, 2011, Pacific Grove, USA – Chapter 3;
- *25º Congresso da Associação Nacional de Pesquisa e Ensino em Transportes* (XXV ANPET), November 7-11, 2011, Belo Horizonte, Brazil – Chapter 5;
- *9º Encontro do Grupo de Estudos em Transportes (9º GET)*, January, 5-6, Tomar, Portugal – Chapters 2, 3, 4 and 5;
- *The Israeli Operations Research Society Conference 2012* (ORSIS 2012), June 3-4, 2012, Jerusalem, Israel – Chapter 6;

- *13º Workshop da Associação Portuguesa para o Desenvolvimento Regional: Policy Analysis of Complex Transport Systems*, June 9, 2012, Ponta Delgada, Portugal – Chapter 5;
- *E3 Forum: Education, Employment and Entrepreneurship* (), June 28, 2012, Lisbon, Portugal – Chapters 5 and 6.

Chapter 2

Optimal Slot Allocation in Publicly-Controlled Aviation Network: an application to Portugal

2.1 Introduction

Airport congestion is one of the main problems faced today by the air transportation industry. In the long-term, this problem may be coped with through the expansion of existing airports (runways and/or terminal buildings) and the construction of new ones, as well as through the improvement of air traffic control systems. However, in the short-term, it is necessary to enhance the utilization of the existing airport capacity – in particular, by allocating airport slots to flights in a more efficient way. Indeed, the outcomes that slot allocation processes are currently leading to appear to be far from optimal from the social point of view (BRUECKNER and ZHANG, 2001; MADAS and ZOGRAFOS, 2006; MARQUES and BROCHADO, 2008).

In this chapter, is presented an optimization model to determine the best possible slot allocation decisions for a publicly-controlled aviation network and, more generally, the best possible design for that type of aviation network. The objective is to minimize the total social costs of satisfying a given leg-based air travel demand with a given aircraft fleet (the fleet of the airlines operating in the network). The costs to minimize include flight costs, airport costs, time costs, congestion costs, and spill costs. The model is intended as a tool for assisting aviation authorities in their decisions regarding slot allocation processes.

Airport slot allocation and, in general, airport capacity utilization have been studied for the last 50 years. NEWELL (1979) analyzed how airport capacity depends of various factors – aircraft mix, departure and arrival flight times, and runway geometry – computing the "airport capacity curve" for an uneven mix of flight departures and arrivals. In the 1990s, this concept has been used in optimization models to define runway (ground) capacity (GILBO, 1993) and runway and near-terminal airspace capacity (GILBO, 1997) for individual airports. In recent years, these models have been extended to multi-airport networks by DELL'OLMO and LULLI (2003) and ANDREATTA et al. (2011), respectively for a deterministic and a stochastic context (to take into account e.g. uncertainty in weather conditions). The objectives considered in these models are the minimization of arrival and departures queues and the minimization of delays.

The previous (single and multi-airport) optimization models determine airport capacity assuming the number of flight arrival and departures to be known. In our model, however, airport capacity is an input parameter. Indeed, we aim to design the aviation network that minimizes the total social costs of satisfying a given passenger demand, and, more specifically, how the slots of the airports included in the network should be allocated to flights.

The remainder of the chapter is organized as follows. In the next section, are presented and discussed the main ingredients of airport slot allocation problems. Afterward, is described the optimization model formulated to deal with such problems in a publicly-controlled aviation network. The practical usefulness of the model in then illustrated with an application to the main aviation network of Portugal. In the final part of the Chapter, are made some concluding remarks and indicated the direction for future work in this area.

2.2 Problem Ingredients

Over the last three decades, air transportation went through a deregulation process that will most probably continue in the next decades (BELOBABA et al., 2009). Within this process, the role of governments (or aviation authorities on their behalf) has changed considerably, especially in the US and in Europe (GOETZ and GRAHAM, 2004, ALVES and BARBOT, 2008). Despite this, air transportation is still controlled very strictly in a vast majority of the world. Indeed, according to IATA (2007), only 17% of the international traffic takes place in a deregulated environment. Moreover, cabotage rights, which are the rights for an airline to transport passengers on the domestic routes of foreign countries, exist only in the European aviation space. This signifies that, at present, governments still occupy a key position in air transportation worldwide and even more so with respect to domestic networks.

The level of control exerted by a government over an aviation network varies considerably from country to country. Sometimes, the government (or some public entity) owns the airports included in the network and also the airline(s) that operate there, thus having full control over the network – in the sense that it can define flight schedules and airport slots (that is, airport capacity utilization). In other cases, the airports are owned by the government but at least some airline operating in the network is not. The level of control in these circumstances is lower, as the government can only define the airport slots and try to influence flight schedules (by way of its regulatory powers and in the framework of bilateral agreements with other governments within which the flight frequencies of the airlines are defined). Finally, if the government does not own airlines and airports, it will not be able to define airport slots, and its level of control over the aviation network will be much smaller.

The focus of this chapter is on the problem faced by aviation authorities willing to allocate airport slots in the aviation network under their control (or influence) with the objective of minimizing the total social costs associated with the operation of the network, while satisfying a given air travel demand and taking into account the aircraft fleet assigned to the flights that take place within the network (regardless of the number of airlines involved).

Slot allocation processes are the processes through which the declared capacity of airports is distributed among the airlines that use the airports. They are promoted by IATA (except in the US) to define the departure and arrival times for the flights of both incumbent airlines and new airlines willing to use the airports. The declared capacity of an airport is "the number of aircraft movements per hour that an airport can accommodate at a reasonable level of service" (DE NEUFVILLE and ODONI, 2003). It depends on the capacity of runways, passenger terminals, and apron areas, as well as on possible environmental constraints and on the intended level of service.

Air travel demand can be given (or estimated) by flight leg (leg-based demand) or by itinerary (itinerary- or O/D-based demand). Itinerary-based demand certainly is more relevant for analyses conducted by airlines, but for network-wide analyses the consideration of leg-based demand should be accurate enough and facilitates the collection of data (statistics on itinerary-based demand are not freely available). The distribution of demand varies considerably over the day. It typically refers to relatively large periods – e.g. early morning, late afternoon, etc. If some fraction of the demand for some period cannot be satisfied, it is expected that part of that demand is recaptured on later periods and the other part is lost, that is, passengers are spilled (BARNHART et al., 2002; RATLIFF et al., 2008; GALLEGO et al., 2010). The fraction of lost demand is typically larger for short-distance flights, that is, travel time elasticity is lower for short-distance flights (see e.g. JORGE-CALDERÓN, 1997).

The total social costs involved in an aviation network consist of five components: flight costs, airport costs, time costs, congestion costs, and spill costs. Flight costs comprise fuel costs and crew costs, as well as vehicle maintenance and depreciation costs. These costs are leg-specific and aircraft-specific (and also airline-specific, since some competitive advantages are expected from one airline over the others). Airport costs include capital and manpower, being different between domestic and international flights. Time costs are the costs associated with the scheduled travel times incurred by the passengers, which mainly depend on the value of time (VOT) and on travel distance. The VOT is higher for business trips than for leisure trips, and increases with passengers' income (BRONS et al., 2002). Congestion costs are the costs for passengers, airlines, and airports related with high levels of airport utilization. Indeed, airport congestion can be neglected for low utilization rates but it tends to increase fast for utilization rates above 80-85% (DE NEUFVILLE and ODONI, 2003). Spill costs represent the loss in revenue (and of good will) that occurs when the existing demand cannot be fully satisfied, either because of lack of seat capacity in the flights or because of mismatches between scheduled travel times and passengers' desired travel times.

2.3 Optimization Model

The model developed to determine the optimal allocation of slots in a publicly-controlled aviation network is presented in this section. There are a few models where aviation network design is dealt with from the perspective of aviation authorities (e.g., JANIC, 2003, and LE et al., 2008), but they do not focus on slot allocation issues. In contrast, there is a vast literature where the subject is coped with from the perspective of airlines. Within this literature, two main problems are considered: flight scheduling and fleet assignment. These problems are often tackled separately – see e.g. ERDMANN et al. (2001), AGBOKOU (2004), and YAN and CHEN (2007) for the flight scheduling problem, and ABARA (1989), HANE et al. (1995) and BARNHART et al. (2002) for the fleet assignment problem. But there are a number of articles where they are dealt with simultaneously through integrated models – see e.g. DESAULNIERS et al. (1997), REXING et al. (2000), and LOHATEPANONT and BARNHART (2004). Our model has a number of features in common with these models but it focus on the optimal utilization of airport capacity rather than on the optimal planning of airline operations.

For formulating the model, consider the following notation:

Sets

- $\boldsymbol{A} = \{1, \ldots, A\}$: set of airports
- $\boldsymbol{P} = \{1, \ldots, P\}$: set of travel demand periods
- $\boldsymbol{T} = \{1, \ldots, T\}$: set of slot time windows (of, say, 15 minutes)
- $\boldsymbol{F} = \{1, \ldots, F\}$: set of aircraft types

Parameters

- s_{Ajt} : capacity of airport j in slot time window t
- n_f: number of aircraft of type f
- s_f: capacity of an aircraft of type f (passengers or seats)
- d_{jk}: scheduled travel time between airports j and k (measured in slot time windows**)**
- q_{jkp}: demand for flights on leg jk (between airports j and k) in period p (passengers)
- α_{jk} : recapture rate (fraction of demand transferred to the next demand period because of lack of aircraft or airport capacity)

- c_{Fjkf}: flight cost for an aircraft of type *f* on flight leg *jk* (EUR per flight)
- c_{Ajf}: airport cost for an aircraft of type *f* in airport *j* (EUR per flight)
- c_{Tjk}: time cost for flight leg *jk* (EUR per passenger)
- r_{jt}: utilization rate at airport *j* in slot time window *t*
- β_j : airport congestion utilization rate at airport *j* (that is the utilization rate of the airport above which congestion delays start to occur)
- c_{Cj}: congestion cost at airport *j* when the utilization rate is 100% (EUR per slot time window)
- c_{Sjk}: spill cost for flight leg *jk* (EUR per passenger)

<u>Decision variables</u>

- x_{jkft}: number of flights by aircraft type *f* on leg *jk* that take off in slot time window *t*
- y_{jft}: number of aircraft of type *f* that are ready to take off from airport *j* in slot time window *t*
- u_{jt}: difference between the utilization rate of airport *j* in time window *t* and airport congestion utilization rate (β_j)
- v_{jt}: binary variable that is equal to 1 if airport *j* is congested in time window *t*, and is equal to zero otherwise
- w_{jkp}: spare seats on flight leg *jk* in demand period *p*
- z_{jkp}, spilled passengers on flight leg *jk* in demand period *p*

Given this notation, the optimization model can be formulated as follows:

$$\begin{aligned}\min\ C = & \sum_{j,k\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} \sum_{t\in \boldsymbol{T}} c_{Fjkf}\, x_{jkft} + \sum_{j\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} \sum_{t\in \boldsymbol{T}} c_{Ajf}\, x_{kjft} + \\ & + \sum_{j,k\in \boldsymbol{A}} c_{Tjkf} \left(\sum_{f\in \boldsymbol{F}} \sum_{t\in \boldsymbol{T}} x_{jkft} s_f - \sum_{p\in \boldsymbol{P}} w_{jkp} \right) \\ & + \sum_{j\in \boldsymbol{A}} \sum_{t\in \boldsymbol{T}} c_{Cjt} \left(u_{jt} + \beta_j v_{jt} \right) + \\ & + \sum_{j,k\in \boldsymbol{A}} c_{Sjk} \left[\sum_{p\varepsilon \boldsymbol{P}} \left(1-\alpha_{jk}\right) z_{jkp} + z_{jkP} \right]\end{aligned} \tag{2.1}$$

$$\sum_{k\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} x_{jkft} + x_{kjm,t-d_{kj}} \le s_{Ajt}\ , \forall j \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{2.2}$$

$$\sum_{j\in \boldsymbol{A}} y_{jft} + \sum_{j,k\in \boldsymbol{A}} x_{jkft} + \sum_{j,k\in \boldsymbol{A}} \sum_{\substack{r\in \boldsymbol{T} \\ r<t, u+d_{jk}>t}} x_{jkfr} = n_f\, , \forall f \in \boldsymbol{F}, t \in \boldsymbol{T} \tag{2.3}$$

$$y_{jf,t-1} - \sum_{k\in \boldsymbol{A}} x_{jkft} + \sum_{k\in \boldsymbol{A}} x_{kjf,t-d_{kj}} = y_{jft}, \forall j \in \boldsymbol{A}, f \in \boldsymbol{F}, t \in \boldsymbol{T} \mid t > 1 \tag{2.4}$$

$$y_{jf1} - \sum_{k\in \boldsymbol{A}} x_{jkf1} + \sum_{k\in \boldsymbol{A}} x_{kjf,T-d_{kj}} = y_{jft}, \forall j \in \boldsymbol{A}, f \in \boldsymbol{F} \tag{2.5}$$

$$\sum_{f\in \boldsymbol{F}} \sum_{t\in \boldsymbol{P}} x_{jkft} \times s_f + z_{jkp} - w_{jkp} = q_{jkp} + \alpha_{jk} \times z_{jk,p-1}, \forall j,k \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{2.6}$$

$$u_{jt} \ge \frac{1}{s_{Ajt}} \left(\sum_{k\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} x_{kjft} + x_{kjf,t-d_{kj}} \right) - \beta_j\, , \forall j \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{2.7}$$

$$v_{jt} \ge u_{jt}, \forall j \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{2.8}$$

$$x_{jkft}, y_{jft} \text{ non-negative integer numbers}, \forall j,k \in \boldsymbol{A}, f \in \boldsymbol{F}, t \in \boldsymbol{T} \tag{2.9}$$

$$z_{jkp}, w_{jkp} \text{ non-negative real numbers}, \forall j, k \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{2.10}$$

$$u_{jt} \text{ real numbers}, \forall j \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{2.11}$$

$$v_{jt} \in \{0,1\}, \forall j \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{2.12}$$

The objective-function (2.1) of this mixed-integer optimization model expresses the minimization of the total social costs involved in the operation of the aviation network, considering the five types of costs identified above (i.e., flight costs, airport costs, time costs, congestion costs, and spill costs). Flights costs are given by the multiplication of the number of flights by their cost per leg and aircraft type. Airport costs are given by the multiplication of the number of flights by a unit cost per flight (arrival or departure), for each airport and aircraft type. Time costs are obtained through the multiplication of the number of passengers in the legs by the respective flight time cost. Congestion costs for each airport j and slot time window t, are given as a linear function of the airport utilization rate. Below a given limit (β_j), it is assumed that congestion is not relevant, u_{jt} is negative, and the binary variable v_{ft} can take the value of zero (and will take it because, otherwise, costs would be higher). Above that limit u_{jt} is positive and v_{jt} will be equal to one and congestion costs are taken into account. For better accuracy, congestion costs could be represented with a piecewise linear function. This would, at the same time, keep the model linear and allow for congestion costs to increase more than proportionally with the airport utilization rate. Finally, spill costs are set equal to the number of spilled passengers multiplied by a unit spill cost. The number of spilled passengers is the difference between the number of passengers that could not travel in the demand period where they would have liked to do it and the number of these passengers that traveled in subsequent demand periods.

The model includes twelve sets of constraints. Capacity constraints (2.2) ensure that movements do not exceed airport capacity (available slots per slot time window). Availability constraints (2.3) describe the use of the existing fleet – for each type of aircraft, the total fleet is equal to the number of airborne aircraft plus the aircraft scheduled to take off plus the parked aircraft. Continuity constraints (2.4) and (2.5) ensure that the number of aircraft of each type available to fly in each time window from each airport is equal to the number of landings minus the number of take-offs in that time window plus the aircraft that were parked in that airport in the previous time window. The demand equation (2.6) states that the total demand for each flight leg and period is either satisfied or spilled. The total demand consists of the passengers that want to travel in that period plus the passengers that were recaptured from the previous period. The satisfied demand is given by the available seats less the spare seats. Utilization constraints (2.7) and (2.8) specify the utilization rate of each airport in each time window and the corresponding level of congestion costs. Finally, statements (2.9) to (2.12) define the domain for the decision variables.

2.4 Case study

The model described in the previous section was used in a case study involving the Portuguese main network of airports. This network consists of five airports: Lisbon (LIS), Oporto (OPO), Faro (FAO), located in mainland Portugal; Funchal (FNC), located in the island of Madeira; and Ponta Delgada (PDL), located in the island of São

Miguel (Azores). All these airports are operated by ANA, a company owned by the Portuguese government. Up to October 2008, only two publicly-owned airlines were operating in the domestic network: TAP and SATA. TAP is owned by the Portuguese government and SATA is owned by the Azorean regional government. In the last few years, EasyJet and Ryanair started operating domestic routes, respectively, Lisbon-Funchal and Oporto-Faro.

The case study consisted in determining the optimal allocation of airport slots (and underlying aviation network design) for the domestic network in the year 2008, a time when it was still fully controlled by public entities, and comparing it with the actual allocation of slots in that year. In addition to this, a sensitivity analysis was conducted to assess the effects of changes in some key parameters on the final results. The case study was carried out to demonstrate, with a simple case, the potential usefulness of the proposed optimization model.

Below, in consecutive subsections, we provide detailed information on the data set used in the case study, on the results obtained through the application of the optimization model (optimal network) and for the sensitivity analysis, and on model solving issues.

2.4.1 Data Set

The data set used in the case study consisted of: capacity of airports; type and number of aircraft; air travel demand and recapture rate; flight duration; costs; and actual network. This data was essentially taken from the official aviation statistics (ANA, 2009) and from the websites of the airports and of the airlines.

The hourly capacity of the airports, shown in Table 2.1, was assumed to be the declared capacity of the airports (the capacity for the 15-minute slot time windows was assumed to be 25% of the hourly capacity). The percentage of airport capacity that could be used for domestic flights was set equal to the percentage of domestic movements in the total movements of each airport during the year 2008.

Table 2.1 - Capacity of airports

Airport	Capacity (movements per hour)		
	Total	International	Domestic
LIS	36	28	8
OPO	20	16	4
FAO	22	18	4
FNC	14	10	4
PDL	14	10	4

There were three types of aircraft making domestic flights in Portugal in 2008: Embraer ER4, Fokker F100, and Airbus A319. The number of available aircraft and the number of seats per aircraft type, as well as the landing fees levied by each airport per aircraft type are presented in Table 2.2.

Table 2.2 - Fleet and landing fees

Aircraft type	Number of aircraft	Seats	Landing fees (EUR)				
			LIS	OPO	FAO	FNC	PDL
ER 4	6	49	170	110	110	225	77
F 100	4	99	214	214	214	445	152
A 319	4	132	315	315	315	653	223

The daily travel demand for each flight leg is given in Table 2.3. This demand was taken to be the number of passengers transported in March 2008 (the busiest winter month in that year) increased by 5%. The number of passengers in that month was 10% of the annual total. The daily demand was divided into four periods – 6 to 10 am, 10 am to 2 pm, 2 to 6 pm, and 6 pm to midnight. Due to lack of data, it was assumed that the daily demand is evenly distributed across those demand periods. The recapture rate between demand periods was considered to be 50% (JA et al., 2001).

Table 2.3 - Leg-based demand

Origin	Leg-based demand (passengers per day)				
	Destination				
	LIS	OPO	FAO	FNC	PDL
LIS	0	960	410	1790	720
OPO	980	0	0	510	180
FAO	420	0	0	0	0
FNC	2110	524	0	0	74
PDL	860	210	0	61	0

The duration of each flight leg is given in Table 2.4. It comprises the time the aircraft is expected to be airborne plus a turn time of 30 minutes (2 slot time windows). After the turn time, it is assumed that the aircraft is ready for take-off or is parked.

Table 2.4 - Flight duration

Origin	Flight duration (15-min slot time windows)				
	Destination				
	LIS	OPO	FAO	FNC	PDL
LIS	-	6	5	9	12
OPO	6	-	7	10	12
FAO	5	7	-	9	12
FNC	9	10	9	-	10
PDL	12	12	12	10	-

The flights costs per leg and aircraft type are shown in Table 2.5 (they were taken from JANIC, 2003). The time costs were calculated considering the value of time to be 15 EUR per hour for all flights – this was approximately the value used in the cost-benefit evaluation of high-speed rail projects in Portugal (TIS.pt, 2007; SDG, 2009).

Table 2.5 - Flight costs

Origin	Flight costs (EUR per passenger)				
	Destination				
	LIS	OPO	FAO	FNC	PDL
LIS	-	23	22	63	94
OPO	23	-	41	75	96
FAO	22	41	-	58	97
FNC	63	75	58	-	74
PDL	94	96	97	74	-

The congestion costs were assumed to be zero for airport utilization rates below 85%, and to grow linearly between 85 and 100% until 1,500 EUR per slot time window (in accordance with the indications given in DE NEUFVILLE and ODONI, 2003). The cost of a spilled passenger was assumed to be very large in relation to the other costs, so that the maximum possible demand is met.

The actual network operated by TAP and SATA before October 2008 (assuming the best possible fleet assignment) is represented in Figure 2.1.

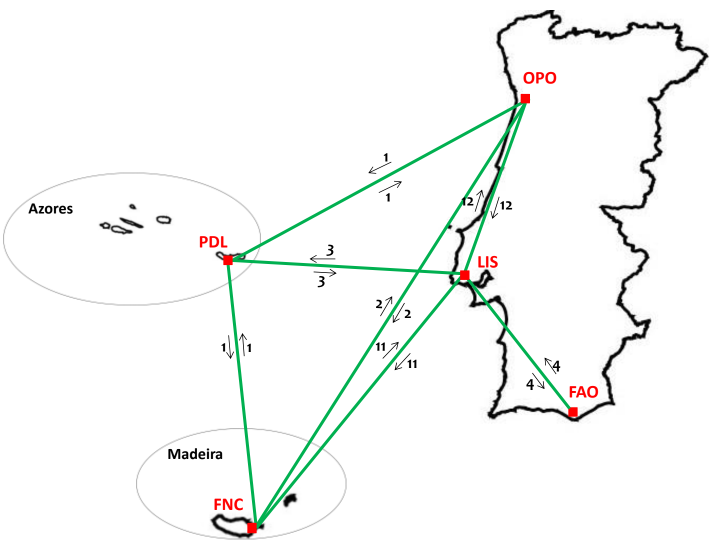

Figure 2.1 - Actual network

The total number of daily flights is 68, thus the number of slots used is 136 slots. The number of passengers transported in the network is 7,982, which signifies 1,827 spilled passengers. The total cost of this network is 1.55×10^6 EUR per day. Congestion affects all airports resulting in a cost of 63,045 EUR.

2.4.2 Optimal Network

The network obtained through the application of the optimization model is described in Figure 2.2 and Table 2.6. In this table, is provided a comparison between the optimal network and the actual network operated by TAP and SATA before October 2008.

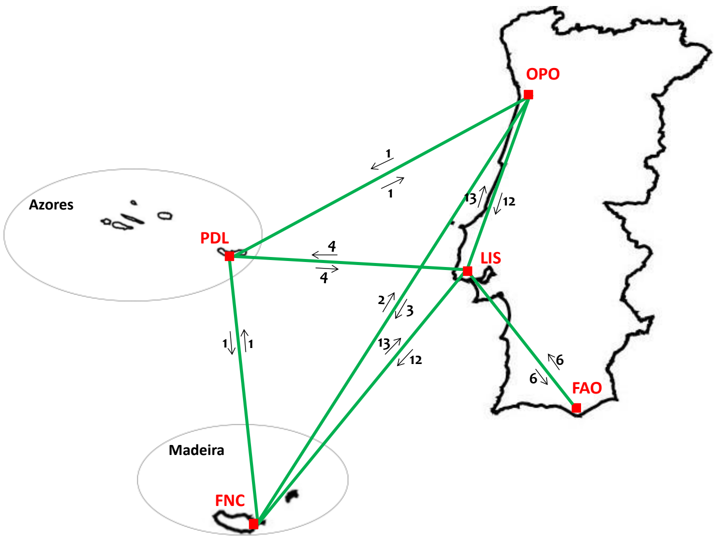

Figure 2.2 - Optimal network

The analysis of the networks reveals that the overall airport utilization is larger in the optimal network, as the slots increase from 138 in the actual network to 158. This is a consequence of the increase in flights from 68 to 79 (+16.2%). The number of passengers transported in the network increases by 6.8% and the number of spilled passengers decreases by 29.7%.

Table 2.6 - Results for the actual and the optimal network

Parameters		Network	
		Actual	Optimal
Number of flights	Value	68	79
	Var. %	-	16.2
Number of passengers	Value	7982	8524
	Var. %	-	6.8
Number of spilled passengers	Value	1827	1285
	Var. %	-	-29.7
Total costs* (K EUR)	Value	1553.2	1533.6
	Var. %	-	-1.3
Flight costs (K EUR)	Value	1278.2	1286.9
	Var. %	-	0.7
Airport costs (K EUR)	Value	15.9	18.4
	Var. %	-	15.8
Time costs (K EUR)	Value	196.0	217.5
	Var. %	-	10.9
Congestion costs (K EUR)	Value	63.0	10.8
	Var. %	-	-82.9

* Net of spill costs

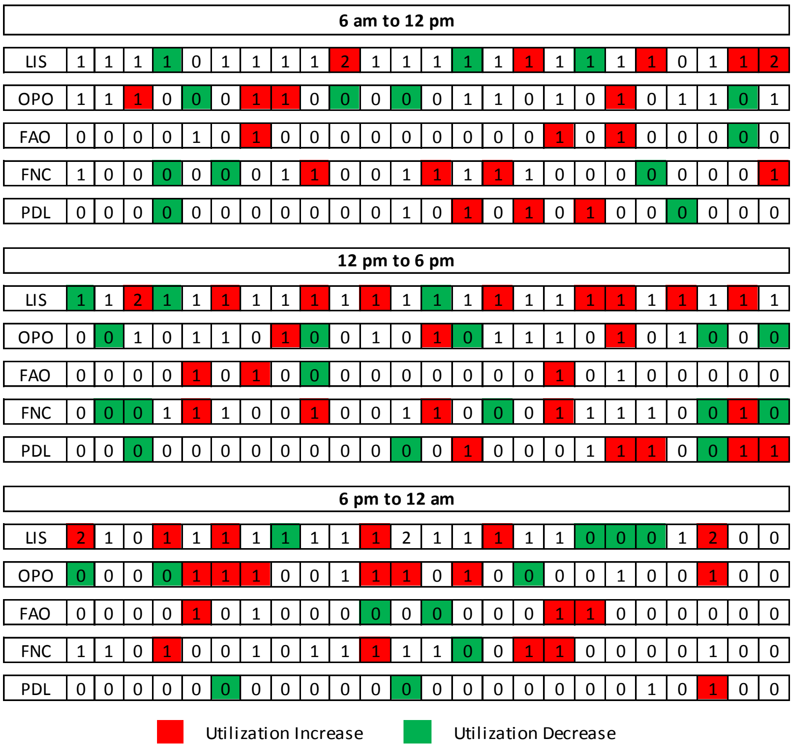

Figure 2.3 - Airport slot utilization for the optimal network

The number of flights augments mainly in the legs connecting Lisbon with the other airports (Figure 2.4). The largest increase occurs in the Lisbon-Faro connection with 6 daily flights each way instead of 4. Also, there are two additional Lisbon-Funchal flights (13 instead of 11). All flight legs except Funchal-Ponta Delgada experiment a reduction with respect to number of spilled passengers, being Lisbon-Faro the leg with the largest reduction (-34.6%).

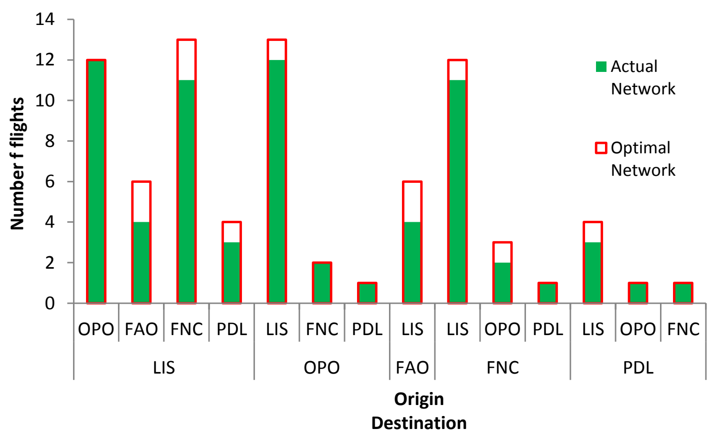

Figure 2.4 - Flight frequencies for the actual network and the optimal network

The 20 aircraft available needed to operate the actual network are also necessary in the optimal network. There are, however, some differences in aircraft utilization, with an increase in the use of medium aircraft and a reduction in the use of large and small aircraft. Indeed, the 99-seater Fokker is the most used aircraft in the optimal network, totaling 39 flights, that is 49% of the total number of flights (against 38% in the actual network). The smallest aircraft (ER 4 with 49 seats) are used in the flights to/from Faro and in 3 flights between Lisbon and Oporto, which represent 18% of the flights instead of 25% in the actual network. The large aircraft are mainly used in the legs connecting mainland Portugal with Azores and Madeira.

Finally, despite the increase in the number of flights and passengers, the optimal network involves a total social cost of 1.53×10^6 EUR (per day), 1.07% lower than the cost of the actual network. Congestion effects are only felt in one airport (Oporto), and their costs drop by 82.9% to 10,800 EUR. Landing fees increase 15.8% as a result of the increase in the number of flights.

2.4.3 Sensitivity Analysis

In order to assess the variability of results, a sensitivity analysis was performed with respect to the following parameters: recapture rate; airport congestion utilization rate; value of time; and spill costs. Table 2.7 provides the results of the sensitivity analysis and comparisons with the results obtained for the actual network and the optimal network.

2.4.3.1. Recapture rate

Four different values of α were tested to evaluate the influence of the recapture rate on the results obtained for the optimal network: 0; 25; 75; and 100%. Large values of α mean that a relatively large number of passengers still want to travel after their preferred travel period. If α is small, then passengers are more time sensitive and less willing to change their travel period.

The conclusion was that the number of slots increases with the value of α, varying between 150 (α = 100%) and 160 (α = 0%), which corresponds to a number of flights between 75 and 80, respectively. In contrast, the number of passengers increases and the number of spilled passengers decreases significantly – for α = 100% the number of spilled passengers is 997, that is, -22.4% than in the optimal network. The total cost of the network ranges between 1.70×10^6 EUR for α = 0 (+10.6% than in the optimal network) and 1.51×10^6 EUR for α = 100% (-1.6%). The largest differences with respect to the optimal network occur for the congestion costs, which vary between +24.3% for α = 0 and -26.1% for α = 100%.

2.4.3.2. Airport congestion utilization rate

The analysis of how changes in airport congestion utilization rate (that is, the airport utilization rate above which congestion effects are felt) affect results was made considering the following β values: 0, 20, 40, 60, and 100%. If β is smaller the congestion effects will be higher and thus the total cost of the network is expected to increase.

It was found that the number of flights varies between 76 and 81 flights, corresponding to 152 and 162 slots, respectively for β = 0 and β = 100%. The total number of passengers is only very slightly affected by changes in β, ranging between 8,520 (when no congestion effects are not felt, that is β = 100%) and 8,540 passengers. The main impact of changes in β relates, naturally, with congestion costs. These costs increase 11 times with respect to the optimal network when β = 0. However, because congestion costs are small in the network under analysis, total costs vary only between 1.61×10^6 EUR (+4.8%) for β = 0 and 1.53×10^6 EUR (-0.4%) for β = 100%.

2.4.3.3. Value of time

The evaluation of the influence of changes in the value of time (VOT) on the results was assessed considering the following alternatives: -20%, -10%, +10%, and +20% of the VOT values used in the calculation of the actual and optimal networks (15 EUR per hour).

The outcome was that the number of slots only varies between 156 (VOT = -10 or -20%) and 158 (VOT = -10 or -20%), which corresponds to 78 or 79 flights. The time costs accompany the variation of the VOT, but this has no implications on the number of passengers (due to the large value of spill costs). The total costs range between 1.51×10^6 EUR (VOT = -20%) and 1.58×10^6 EUR (VOT = +20%), that is, respectively, -1.4% and +2.8% than the cost for the optimal network.

2.4.3.4. Spill costs

The optimal network was calculated assuming a very large cost per spilled passenger, so that the maximum possible demand is satisfied. This assumption is now relaxed, as two unit spill costs are considered: the average airfare per leg; and the double of this average.

The implications of these changes is that the number of slots decreases to 142 (-10.1%) and 146 (-7.6%), respectively for the average airfare and for the double of the average airfare, the number of flights decreases by the same percentages, and the number of passengers drops by 6.3 and 5.5%. Although these values are lower than for the optimal network they are still higher than for the actual network. The decrease in flights and passengers is reflected on flight and time costs. Flight costs decrease 14.3 and 11.6% while time costs drop 10.7 and 8.3%. The total costs (net of spill costs) are 1.32×10^6 EUR for the average airfare and 1.36×10^6 EUR for the double of the average airfare, that is, 13.7 and 11.1% lower than the total costs for the optimal network.

Table 2.7 - Results for the sensitivity analysis

Network		Number of flights		Number of passengers		Number of spilled passengers		Total costs* (K EUR)		Flight costs (K EUR)		Airport costs (K EUR)		Time costs (K EUR)		Congestion costs (K EUR)	
		Value	Var.%	Value	Var.%	Value	Var.%	Value	Var.%	Value	Var.%	Value	Var.%	Value	Var.%	Value	Var.%
Actual		68	-	7982	-	1827	-	1553.2	-	1278.2	-	15.9	-	196.0	-	63.0	-
Optimal		79	16.2	8524	6.8	1285	-29.7	1533.6	-1.3	1286.9	0.7	18.4	15.8	217.5	10.9	10.8	-82.9
Recapture rates (%)	0	80	1.3	8104	-4.9	1705	32.7	1695.6	10.6	1423.9	10.6	19.4	5.3	238.9	9.9	13.4	24.3
	25	79	0.0	8256	-3.2	1553	20.9	1647.4	7.4	1383.9	7.5	19.3	4.9	232.6	7.0	11.5	6.0
	75	78	-1.3	8783	3.0	1026	-20.1	1526.3	-0.5	1280.9	-0.5	18.0	-2.2	217.5	0.0	9.9	-8.3
	100	75	-5.1	8813	3.4	996	-22.5	1508.8	-1.6	1266.9	-1.6	16.4	-10.8	217.5	0.0	8.0	-26.1
Airport congestion utilization rate (%)	0	76	-3.8	8520	0.0	1289	0.3	1607.0	4.8	1252.8	-2.7	16.7	-9.3	207.7	-4.5	129.8	1102
	20	77	-2.5	8525	0.0	1285	0.0	1564.7	2.0	1223.2	-4.9	17.2	-6.5	208.5	-4.1	115.7	972
	40	77	-2.5	8515	-0.1	1294	0.7	1565.7	2.1	1279.1	-0.6	18.6	1.1	209.9	-3.5	58.0	437
	60	78	-1.3	8525	0.0	1284	-0.1	1540.3	0.4	1271.0	-1.2	18.0	-2.6	209.7	-3.6	41.6	285
	100	81	2.5	8540	0.2	1269	-1.3	1527.5	-0.4	1303.3	1.3	19.0	3.2	205.1	-5.7	0.0	-100
Time costs (%)	-20	78	-1.3	8524	0.0	1285	0.0	1511.7	-1.4	1311.6	1.9	18.5	0.3	170.8	-21.5	10.8	0.0
	-10	78	-1.3	8523	0.0	1286	0.1	1535.4	0.1	1311.6	1.9	18.5	0.3	194.4	-10.6	10.8	0.0
	+10	79	0.0	8522	0.0	1287	0.2	1551.0	1.1	1286.9	0.0	18.4	0.0	234.9	8.0	10.8	0.0
	+20	79	0.0	8524	0.0	1285	0.0	1577.1	2.8	1286.9	0.0	18.4	0.0	261.0	20.0	10.8	0.0
Spill costs	Avg. fare	71	-10.1	7991	-6.3	1818	41.5	1324.2	-13.7	1102.9	-14.3	17.0	-7.7	193.5	-11.0	10.8	0.0
	2 x Avg. fare	73	-7.6	8053	-5.5	1756	36.7	1363.9	-11.1	1137.6	-11.6	17.5	-5.2	198.0	-8.9	10.8	0.0

* Net of spill costs

2.4.4 Model Solving

The optimization model was solved on a Dual Core processor with 1GB of RAM using the Xpress software (FICO, 2009). The optimal network was computed in 356.2 seconds – the LP relaxation took 0.8 seconds, the first feasible integer solution was obtained after 6.4 seconds, and the 1% optimality gap was reached in 15.5 seconds. For all instances solved, the computation time varied between 89.0 seconds and 1,879.4 seconds with an average of 619.2 seconds and standard deviation of 449.9 seconds. The larger computation times occurred when β = 0, that is, when airports experience congestion even for very low utilization rates (Figure 2.5). Apart from this, there seems to be no pattern relating model instances with computation time. The LP relaxation took between 0.6 and 1.9 seconds with an average of 1.2 seconds and a standard deviation of 0.4 seconds. On average, the first integer variable was found after 8.0 seconds (standard deviation of 3.0 seconds) and the 1% optimality gap was reached after 34.7 seconds (standard deviation of 24.7 seconds). For most instances, the 1% optimality-gap solution was the same as the optimal solution.

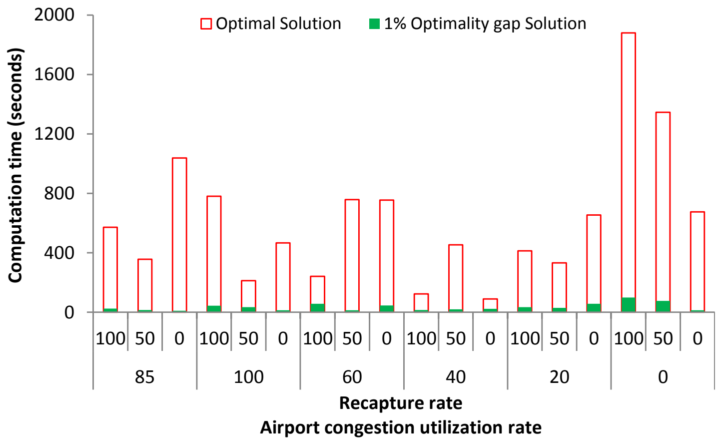

Figure 2.5 - Computation time

The large computation time necessary to solve small instances, like the one raised by the main aviation network of Portugal, clearly indicates that the model will be very hard to solve to exact optimality for large and even mid-size networks. For such networks, if 1% optimality-gap solutions are not accurate enough (even knowing that they quite probably are the optimal solutions), then more efficient formulations and/or methods would have to be developed for tackling the model.

2.5 Conclusions

In this chapter, we presented an optimization model for assisting governments (aviation authorities) in their decisions regarding the allocation of airport slots and, more generally, the design of aviation networks. The results obtained through the model can be fully applied in practice by governments who exert complete control over the aviation network of the respective countries (and, despite the deregulation of air transportation, this is still the case in many parts of the world). If control is only partial, then governments can use the results provided by the model to influence the choices of the other agents involved (airports and/or airlines). The optimization model has a number of features in common with the integrated flight scheduling and fleet assignment models used by airlines for operational planning purposes, but also has some specific features, e.g., airport slots are a decision variable, the objective is to minimize total social costs (including passenger time costs), and congestion costs depend on the decisions made. The practical usefulness of the model was demonstrated through an application to the main aviation network of Portugal in 2008 (the last year it was fully controlled by the government). Indeed, the results obtained for this application show that a different airport slot allocation would have allowed serving a much larger number of passengers while decreasing slightly the total social costs of the network (or, alternatively, serving a slightly larger number of passengers with much lower costs).

With respect to this area of work, our main goal is to improve the model so as to make it more suitable for application to aviation networks that are not fully controlled by governments. This will in particular require taking into account the competition among the airlines and/or airports involved in the networks. Even if competition issues are dealt with in a simplified way, the model would have to be considerably modified in order to properly capture them, posing a research challenge that we plan to address in the near future.

Chapter 3

Optimization-based analysis of Slot Allocation in the main European Airports

3.1 Introduction

Aviation authorities in Europe (EUROCONTROL) and in the United States (FAA) are working on very ambitious programs to increase the capacity of the air transportation system, in order to reduce the current levels of airport delays. These programs focus on air traffic control systems (SESAR and NextGen) and on innovative demand management measures. Such initiatives are necessary to cope with the expected increase in demand for air transportation – "intra-European routes have a forecast growth of passenger demand of 4.0 percent per year until 2031" (BOEING, 2011) – and to diminish the current levels of delays – which represented in 2007 over 32 billion USD just in the US (NEXTOR, 2010). At the European level, the CODA report reveals that in 2010, 44.8 percent of the flights in Europe were delayed at arrival and the average delay time of those flights was 33 minutes (EUROCONTROL, 2011).

To cope with the future demand for air transportation it is necessary to increase system capacity and to regulate the supply-demand relationship (flights and passengers) using administrative or market-based measures. Building new airports, expanding the existing airport capacity – runways and terminals –, and enhancing the air traffic control system are examples of measures to increase system capacity. In the supply-demand relationship side, an administrative slot allocation process is established in the main airports outside the US. Market-based mechanisms are, among others, congestion pricing, airport slot trading, and airport slot auctions, as well as the adoption of a more market-driven landing fee scheme. However, in the short and medium term the air transportation system relies on the improvements that can be achieved by better allocating the existing airport capacity (air traffic control and slot control).

The main objective of the research described in this chapter is to analyze whether airport capacity and slot distribution are capable to accommodate the expected passenger demand with lower costs, including airport delay costs. The approach used for the analysis applies to a liberalized, congested, and slot-constrained air transportation network, being based on an optimization model that determines the minimum total cost for the network (flight frequencies, flight times, seats per leg) taking into account the passenger demand per flight leg, the market power of airlines, and the expected values of airport delays. The fundamental research question to be answered can be formulated as follows:

"Is it possible to satisfy a given passenger demand with less air transportation system

costs (including aircraft and passenger delay costs) without compromising airline competition?"

The chapter is organized as follows. In the next section, we provide some background on the subject of liberalized, congested and slot-constrained air transportation networks. After that, the main European air transportation network (involving 34 airports) is characterized with respect to airport market concentration, capacity utilization, and flight delays. Then, we present the optimization model upon which the approach is based. The usage of the optimization model is illustrated next with a case study involving the ten largest European airports. In the final section, the strengths and limitations of the approach and underlying model are assessed, and the conclusions drawn from the case study are summarized.

3.2 Background Information

Liberalized, mature air transportation networks – especially, Europe and North America – have features and problems that are, to some extent, different from other networks. In particular, these networks involve open markets in which: (1) airlines compete intensely for market power by increasing frequency and lowering fares; (2) airports compete for attracting connecting passengers and to become airline bases and hubs, thus increasing their commercial attractiveness; (3) passenger demand for air transportation has grown significantly more than airport capacity; (4) airport delays are getting higher as airport utilization is getting close to maximum. Thus, today airport capacity is a scarce resource that needs to be used in the best possible way, as delays increase more than proportionally with the increase in airport utilization (DE NEUFVILLE and ODONI, 2003).

Reducing congestion and airport delays is extremely important for the air transportation system because they have a significant impact for passengers that arrive later than expected to their destinations and, particularly, for those that miss their connections, because of the costs for airlines of disrupted schedules and passengers, and also because of the indirect implications for the economy. Not all delays are possible or even desirable to eliminate, as they are derived from a great number of interdependent factors such as air traffic control limitations, lack of airport capacity, airline network configurations, bad weather conditions, security measures, and environmental constraints. Despite this, it seems that airline competition has a strong impact on the existing levels of delays, as carriers compete aggressively for passengers, increasing competition and reducing aircraft seat capacity (especially in the short and medium haul flights).

To cope with the shortage of airport capacity, airlines, airports, slot coordinators, and public authorities under IATA guidance have established a slot allocation system that regulates the use of airport capacity – for details see MADAS and ZOGRAFOS (2008) and IATA (2012). This system limits the usage of airports to a specified number of movements for a given time period. The airport capacity in terms of slots is set administratively taking into account the number of runways, capacity of the terminals, air traffic control capacity, and intended level of service. The core principles of the slot allocation system are the so-called “grandfather rights” and “use-it-or-lose-it” rule. According to them, airlines that have the right to use a slot in a season can keep it in the next if they have used it beyond a given threshold (usually, 85 percent). With these principles, some factors arise that might compromise an efficient use of the airport capacity:

1. In slot constrained airports airlines tend to use all slots they have the right to use in order to keep them for the next season and preventing the entry of competitors.

2. Because of that, airlines with historical market power at an airport tend to keep their advantageous position restricting competition (Figure 3.1) – which is even truer at peak periods (BARBOT, 2004).

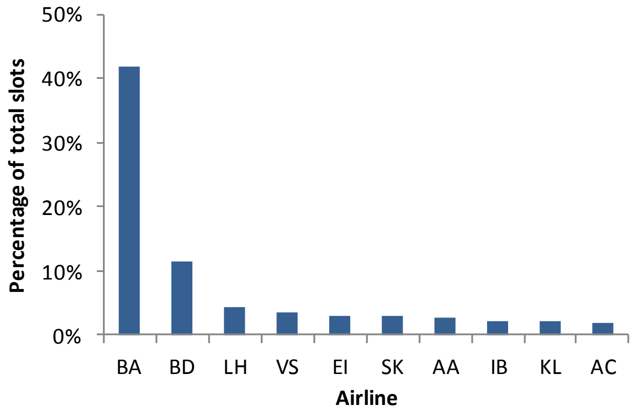

Figure 3.1 - Airline slots at Heathrow Airport (Start of 2009 summer season)

3. When their market power is high, airlines can charge a fare premium (STARKIE, 1998), and tend to increase flight frequency rather than increasing aircraft capacity – "tendency exists that aircraft size is kept below optimal levels" (GIVONI and RIETVELD, 2009).

4. Finally, this contributes for a less-than-total use of airport capacity because

airlines drop slots that are assigned in a period of time different from the requested as the assigned slots are not viable (or profitable) under their network restrictions. This is especially true in airports where demand exceeds capacity only at peak periods (AACHEN UNIVERSITY, 2007).

The air transportation system is thus being operated with a fierce competition between airlines for passengers and revenues and, at the same time, a lack of competition at the airport level. This situation might promote a less than optimal use of airport capacity with consequences in terms of delays and passengers' level of service. These circumstances have been be the basis for a discussion (especially at the European level) of more market-based mechanisms to allocate airport capacity, and the European Commission has produced regulations that go in line with "the needs of the European airports" (CEC, 2011).

There are several measures that can be classified as "market-based mechanisms", such as slot trading, slot auctions, congestion pricing, and landing fees non-proportional to maximum takeoff weight (MTOW), which have been discussed in the literature (PELS and VERHOEF, 2004; JANIC, 2005; DANIEL and HARBACK, 2009). The strengths and limitations of the current slot allocation system and possible impacts on the air transportation system of a shift to market-based mechanisms have been studied in the literature – STARKIE (1998), FAN (2004), BARBOT (2004), and MADAS and ZOGRAFOS (2010) – and in reports centered on the European and US markets – NERA (2004), DOTECON (2006), and NEXTOR (2010).

Due to their importance to the air transportation system, airport delays have been addressed extensively in the literature. The consequences and design of congestion pricing strategies have been dealt with, among others, by BRUECKNER (2002, 2005), SCHANK (2005), and SANTOS and ROBIN (2010). According to SANTOS and ROBIN (2010) "a congestion charge should be set equal to the congestion externality not already internalized by the airlines", which goes in line with the findings from BRUECKNER (2002). The relationship between airport utilization and airport delays has been studied by JOHNSON and SAVAGE (2006), LE (2008), and VAZE and BARNHART (2012), among others. According to VAZE and BARNHART (2012), a reduction in the number of slots at LaGuardia would increase the profits for all the airlines and decrease substantially delay costs. Finally, some studies have focused on the effects of congestion for the passengers, e.g., BRATU (2003), SHERRY et al. (2007), AHMADBEYGI et al. (2008), and BARNHART et al. (2010). Those papers conclude that travel disruptions (cancelled flights and missed connections) are the main cause for passenger delays. According to BARNHART et al. (2010), travel disruptions account for almost half of passenger delay time in 2007.

3.3 Airport Characterization

The characterization of airport market concentration, capacity utilization, and flight delays for the 34 largest European airports (corresponding to the airports analyzed by the CODA reports) was made using data from a week of July 2009 (OAG data). Relevant statistical results are described in the next paragraphs. The analysis was made to support assumptions and hypothesis tested with the optimization model.

The European air transportation network is a liberalized and congested network where European-based airlines have cabotage rights, that is, they are free to provide domestic and international services in any country in Europe. Despite this, legacy carriers still hold a dominant position in the airports of their countries, where they have set their main hubs. This dominance is a factor which is kept by the current slot allocation system based on historical rights – "grandfather rights" – and the "use-ir-or-lose-it" rule.

Airport market concentration was assessed using the Herfindahl–Hirschman Index (HHI). Results show that 20 out of the 34 airports can be considered as market-concentrated (Figure 3.2), and that concentration is related with the market power of the largest airline in each airport and not with the airport size or the average number of seats per flight.

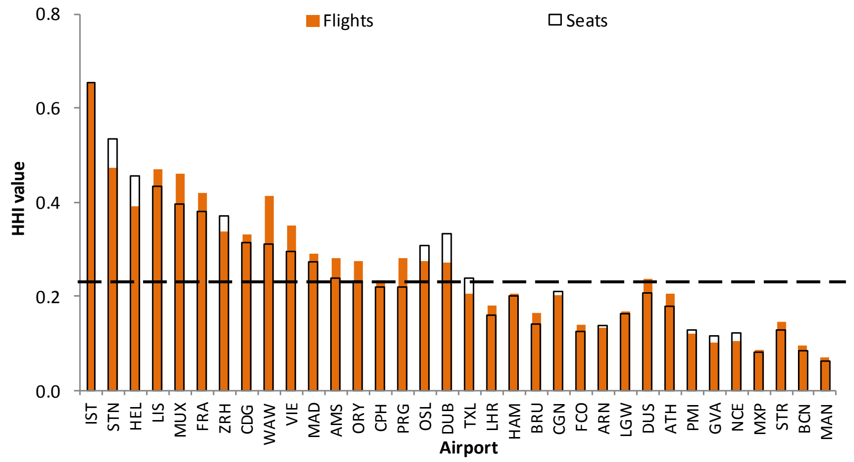

Figure 3.2 - Herfindahl Index (flights and seats) for the 34 biggest airports in Europe (July 2009)

Airport primary delays were estimated using the stochastic and dynamic queuing model DELAYS© (KIVESTU, 1976; MALONE, 1995). To do so, we first calculated the airport utilization rate per 15-min and hour period. Airport utilization rate was defined as the total number of assigned slots divided by the airport declared capacity per period of time. For the 34 airports, the average peak-hour utilization rate is 81.0 percent and the average daily utilization rate is 54.9 percent (Figure 3.3). As can be seen in the figure, only two airports are characterized with an average daily utilization above 80 percent – Frankfurt and London Heathrow – meaning that there is still airport capacity to be used.

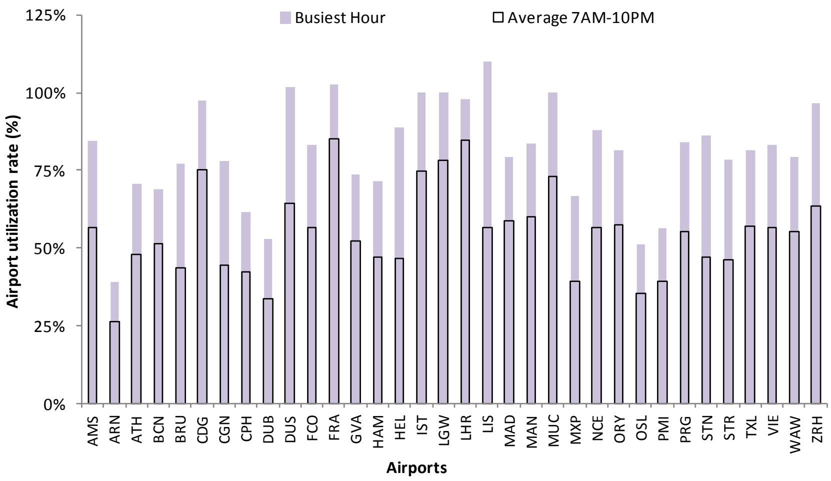

Figure 3.3 - Airport utilization rate per day and busiest hour for the 34 biggest airports in Europe (July 2009)

Airport delays are clearly related with airport utilization (Figure 3.4). The case of London Heathrow shows that when utilization increases the expected primary delay also increases. Taking into account that typically only 40 percent of flights are delayed, the average value per delayed flight is approximately 11 minutes without considering propagation effects in the network. Using the "1+1" average value for propagation effect (COOK and TANNER, 2011) – i.e., one minute of primary delay generates, on average, one minute of reactionary delay – each delayed flight is responsible for over 20 minutes of delay or, in terms of cost, for more than 1,600 EUR.

From the characterization made above, some conclusions can be drawn about the

European network with implications for our analysis: first, most of the airports are market concentrated and dominated by a country-based airline; second, the average number of seats per flight seems to be related with the type of airport but not with airport competition; third, airport delays are relevant especially when airport utilization rate is near capacity; fourth, there is still available airport capacity outside peak hours in all airports.

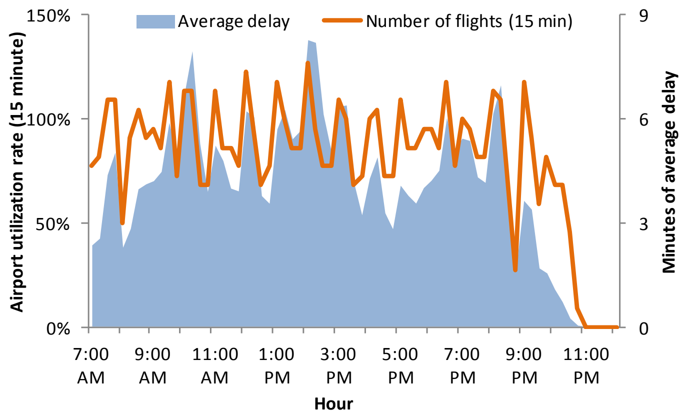

Figure 3.4 - London Heathrow Airport average primary delay and airport utilization rate (July 2009)

3.4 Optimization Model

In this section, we describe the optimization model developed to answer the research question. The objective of the model is to minimize the total cost of an air transportation network. The costs considered in the model are the direct costs to transport passengers from one airport to the others, namely flight costs, airport costs, delay costs, spill costs, and schedule delay costs. Airline competition is taken into account by reallocating slots across airlines in a balanced manner, thus ensuring that changes in airlines' market power will be small.

The model applies to a given planning period – e.g., one day – divided in demand periods within which passenger demand is assumed to be given – e.g., 3-hour periods – and further divided in slot time windows – e.g., 15 minutes. Airport declared capacity (number of available slots) and utilization rate (number of slots assigned to airlines) are known and defined per slot time window. A given number of airlines operate in the system. For each airline, the number and time windows of available slots per airport, as well as the flight frequency and number of passenger per flight leg, are known. Connectivity issues are not addressed in the model.

Using the notation provided in Table 1, the model can be formulated as follows:

$$\begin{aligned}
\min C = & \sum_{j,k\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A}} \sum_{s\in \boldsymbol{S}} \sum_{t\in \boldsymbol{T}} \left(c^{F}_{jks} sx_{jkast} + c^{A}_{js} sx_{kjast} \right) \\
& + \sum_{j,k\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A}} \sum_{s\in \boldsymbol{S}} \sum_{t\varepsilon \boldsymbol{T}} c^{D}_{js} d_{jkt} sx_{jkast} \\
& + \sum_{j,k\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A}} \sum_{t\varepsilon \boldsymbol{T}} c^{T}_{jk} \left(d_{jkt} - t^{P}_{jka} \right) u_{jkat} \qquad (3.1) \\
& + \sum_{j,k\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A}} \sum_{p\varepsilon \boldsymbol{P}} p_{jk} \left(q_{jkap} - \sum_{t\varepsilon \boldsymbol{T_P}} u_{jkat} \right) \\
& + \sum_{j,k\in \boldsymbol{N}} \sum_{a\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} \sum_{p\in \boldsymbol{P}} c^{S}_{jk} sv_{jkafp}
\end{aligned}$$

The objective function (3.1) expresses the minimization of the costs of an air transportation network. The costs considered are, in order of appearance: flight costs and airport costs; aircraft delay costs; passenger delay costs; spill costs; and schedule delay costs. Flight costs are computed as a function of leg distance and average number of seats per flight, leg and airline. Airport costs are calculated as a function of the average number of seats per flight. Aircraft delay costs are calculated by multiplying the

Table 3.1 - Notation for the optimization model

Sets

$\boldsymbol{N} = \{1, \ldots, N\}$ - set of airports

$\boldsymbol{A} = \{1, \ldots, A\}$ - set of airlines

$\boldsymbol{P} = \{1, \ldots, P\}$ - set of demand periods

$\boldsymbol{T} = \{1, \ldots, T\}$ - set of slot time windows

$\boldsymbol{T_P} = \{1, \ldots, T_P\}$ - set of slot time windows belonging to demand period *p*

$\boldsymbol{S} = \{1, \ldots, S\}$ - set of aircraft average sizes (in number of seats)

$\boldsymbol{F} = \{1, \ldots, F\}$ - set of flight frequencies

Parameters

n_{jat} - number of slots of airline *a* at airport *j* in slot time window *t*

t_{jk} - travel time between airports *j* and *k* (in slot time windows**)**

q_{jkap} - demand of airline *c* for leg *jk* in demand period *p*

c^F_{jks} - unit flight cost for aircraft of average size *s* on leg *jk* (EUR per seat)

c^A_{js} - unit airport cost per aircraft of average size *s* at airport *j* (EUR per seat)

c^D_{js} - unit delay cost per aircraft of average size *s* at airport *j* (EUR per seat per minute)

c^S_{jk} - unit schedule delay cost for leg *jk* (EUR per passenger per minute)

c^T_{jk} - unit time cost for leg *jk* (EUR per passenger per minute)

d_{jkt} - expected delay for leg *jk* in slot time window *t* (minutes)

α_{jk} - maximum percentage of passenger demand for leg *jk* that can be lost/gained by each airline

β_{jk} - maximum percentage of passenger demand for leg *jk* that can be spilled

p_{jk} - average fare for leg *jk* (EUR per passenger)

t^P_{jka} - schedule padding for airline *a* on leg *jk* (minutes)

t^D_f - schedule delay for flight frequency *f* (minutes)

Decision Variables

x_{jkast} - number of flights on leg *jk* made by airline *a* with aircraft of average size *s* that take off in slot time window *t*

u_{jkat} - number of passengers on leg *jk* traveling in flights of airline *a* that take off in slot time window *t*

v_{jkafp} - number of passengers on leg *jk* traveling in flights of airline *a* with a frequency of *f* that take off in demand period *p*

$y_{jkasp} = 1$ if aircraft of average size *s* are used by airline *a* on flight leg *jk* and demand period *p* (otherwise $y_{jkasp} = 0$)

$z_{jkafp} = 1$ if airline *a* flies with frequency *f* on leg *jk* and demand period *p* (otherwise $z_{jkafp} = 0$)

average cost per minute of delay by the number of flights and by the expected delay time. Passenger delay costs are calculated by multiplying the average cost per minute of delay of a passenger by the expected delay time minus the average schedule padding and by the number of passengers. Spill costs are the loss in revenue for airlines of not being able to satisfy all passenger demand. They are obtained by multiplying the difference between the passenger demand and the total number of passengers in a leg by the average fare in the leg. Schedule delay costs are calculated by multiplying the average unit passenger waiting time cost by the number of total passengers per leg and demand period and by the average waiting time per leg and demand period.

Ten sets of constraints are included in the model.

Capacity constraints (3.2) restrict the use of an airport for departures and arrivals to the slots available per airline and slot time window. Demand constraints (3.3) specify that the sum of passengers carried by the airlines needs to be at most equal to the passenger demand for that leg. The maximum level of passenger spill is given by constraints (3.4). If β_{jk} is zero then all passenger demand on leg *jk* needs to be satisfied. The maximum amount of passenger demand that each airline can gain or lose with respect to the actual situation is defined by constraints (3.5) and (3.6). These constraints are necessary if passenger transfers between airlines are to be kept within given limits. This is relevant to guarantee that changes with respect to the actual situation are small, thus not changing airlines' market power significantly.

$$\sum_{k \in \boldsymbol{N}} \sum_{s \in \boldsymbol{S}} x_{jkast} + x_{kjas,t-t_{kj}} \leq n_{jat}, \forall j \in \boldsymbol{N}, a \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{3.2}$$

$$\sum_{a \in \boldsymbol{A}} \sum_{t \in \boldsymbol{T_P}} u_{jkat} \leq \sum_{a \in \boldsymbol{A}} q_{jkap}, \forall j,k \in \boldsymbol{N}, p \in \boldsymbol{P} \tag{3.3}$$

$$\sum_{a \in \boldsymbol{A}} \sum_{t \in \boldsymbol{T}} u_{jkat} \geq \beta_{jk} \sum_{a \in \boldsymbol{A}} \sum_{p \in \boldsymbol{P}} q_{jkap}, \forall j,k \in \boldsymbol{N} \tag{3.4}$$

$$\sum_{t \in \boldsymbol{T_P}} u_{jkat} \geq q_{jkap} \times (1 - \alpha_{\mathrm{jk}}), \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{3.5}$$

$$\sum_{t \in \boldsymbol{T_P}} u_{jkat} \leq q_{jkap} \times (1 + \alpha_{\mathrm{jk}}), \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{3.6}$$

The definition of an average number of seats per flight is needed to determine flight and airport costs as a linear function of the aircraft size. For each flight leg, demand period and airline, an average number of seats per flight is determined through constraints (3.7). Constraints (3.8) specify that the number of passengers in each flight leg, demand period and airline cannot exceed the available number of seats. Constraints (3.9) determine the aircraft seat configuration (available number of seats) to be used in each flight leg, demand period, and airline.

$$\sum_{s \in \boldsymbol{S}} y_{jkasp} \leq 1, \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{3.7}$$

$$u_{jkat} \leq \sum_{s \in S} s x_{jkast}, \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, p \in \boldsymbol{P}, t \in \boldsymbol{T_P} \tag{3.8}$$

$$x_{jkast} \leq y_{jkasp}, \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, s \in \boldsymbol{S}, p \in \boldsymbol{P}, t \in \boldsymbol{T_P} \tag{3.9}$$

The average schedule delay in each flight leg and demand period is defined assuming that passenger demand is given in each demand period. Constraints (3.10) define the flight frequency in each flight leg and demand period as the sum of the flights flown on that demand period by all airlines. The total number of passengers in each demand period is defined in constraints (3.11) as the sum of all passengers that fly in flights departing in the slot time windows belonging to the demand period.

$$\sum_{f \in \boldsymbol{F}} fz_{jkafp} = \sum_{s \in \boldsymbol{S}} \sum_{t \in \boldsymbol{T_P}} x_{jkast}, \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{3.10}$$

$$\sum_{f \in \boldsymbol{F}} v_{jkafp} = \sum_{t \in \boldsymbol{T_P}} u_{jkat}, \forall j,k \in \boldsymbol{N}, a \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{3.11}$$

3.5 Case study

The optimization model presented in the previous section was applied to the ten largest European airports in terms of international non-European passengers (excluding the airports dominated by low-cost carriers) and eight major European airlines, using flight and passenger data from July 2009. The airports considered in the application were Amsterdam - Schiphol (AMS), Barcelona - El Prat (BCN), Paris - Charles de Gaulle (CDG), Rome - Fiumicino (FCO), Frankfurt - Main (FRA), London - Gatwick (LGW), London - Heathrow (LHR), Madrid - Barajas (MAD), Munich International (MUC), and Milan - Malpensa (MXP). The airlines dealt with in the application were Air France (AF), British Airways (BA), Iberia (IB), KLM (KL), Lufthansa (LH), SWISS (LX), Austrian Airlines (OS), and EasyJet (U2). A dummy airline was included to account for the rest of the traffic between the airports considered in the application.

Low-cost carriers were not dealt with in the case study despite the fact that some of them are among the largest in Europe in terms of passengers. Three main reasons explain this: they are not dominant players in the busiest and congested airports; they tend to serve a different kind of passenger demand; and they operate flight legs that use airports that were considered secondary just a few years ago – these airports were also not considered in the study.

The study determined the minimum cost, including expected delay costs, to transport a given number of passengers. First, we have calculated the cost of the actual network, which was used to compare with the optimal network. The optimal network was obtained setting α=5% and β=0%, that is, limiting passenger transfers between airlines to 5% and guaranteeing that all passengers were transported.

After obtaining the optimal network, three model alternatives were run to analyze specific aspects:

- Passenger transfer limit effects - the optimization model was run with different values of α to evaluate the impact of this parameter for airline and overall network costs. Six values of α were considered: 0% (no transfer), 5%, 10%, 20%, 50%, and 100% (unlimited transfers).

- Delay cost effects - the optimization model was run without considering delay costs, and these costs were computed afterwards. This permits to assess the impact of delay costs on the airline and network costs and on flight frequencies.

- Flight frequency effects - the optimization model was run fixing the flight frequencies per leg to the actual value. This alternative gives insights about the improvements that can be achieved in the network even without changing flight frequencies.

- Passenger spill effects - the optimization model was run allowing for passenger spill. This permits to evaluate the impact of the passenger spill parameter (β) on airline and network costs and on the passenger level of service. Three values of β were considered: 5%, 10%, and 20%.

The indicators used to compare the actual network with the optimal network were as follows: total costs, flight costs, delay costs (aircraft and passengers), flight frequency, flights per airport, and average number of passengers per flight. The comparison is done, when suitable, per airline and airport.

The data used in the case study is presented in the next sub-section. Then, we describe the results, beginning with the actual network, and continuing with the optimal network and the networks corresponding to each model alternative.

3.5.1 Study Data

To carry out the case study, the following data are needed: airline flight schedules, airport schedules, airport declared capacity, expected delay times per airport, airport landing fees, number of passengers per leg, delay costs for flights and passengers, and average fares per leg. These data were collected from OAG schedule database, EUROCONTROL, and EUROSTAT.

Airline schedules were obtained using OAG database for a week of July 2009, from which we took the busiest day for the case study – Friday. A total of 1,025 flights were considered between the ten airports analyzed. The slot distribution per airline in each airport and slot time window and the average number of seats per leg and airline were also obtained from that database. An overview can be seen on Table 3.2. The flight frequencies and flight times per leg given in Table 3.3 are also for Friday. The flight time per leg was assumed to be the lowest value in the schedule for the leg. The schedule padding of each flight is assumed to be the difference between the scheduled flight time and the minimum flight time.

Table 3.2 - Daily airline slots per airport

Number of Slots										
Airline	Airport									Total
	AMS	BCN	CDG	FCO	FRA	LHR	MAD	MUC	VIE	ZRH	
AF	14	16	126	12	16	14	20	14	8	12	252
BA	12	10	16	10	12	104	10	14	8	12	208
IB	8	84	0	10	8	22	138	8	4	6	288
KL	104	12	14	10	8	16	12	12	8	12	208
LH	28	22	36	24	132	36	16	120	20	22	456
LX	8	6	12	8	10	12	6	8	8	78	156
OS	8	4	6	4	8	8	0	8	54	8	108
U2	0	4	8	0	0	0	4	0	0	0	16
Other	31	80	22	67	20	17	65	11	38	7	358
Total	213	238	240	145	214	229	271	195	148	157	2050

Airport declared capacity was taken from EUROCONTROL reports in movements per hour and then divided in 15-minute periods (Table 3.4). The expected primary flight delay time for each airport and slot time window was obtained using this data through the DELAYS© model (Table 3.4).

Airports costs were assumed to be equal to the landing fees levied by the airports to the airlines. The landing fees were estimated for each airport according to IATA (2009) as a linear function of aircraft seat capacity. An example for Brussels Airport is shown in Figure 3.5.

Table 3.3 - Flight frequency per leg

Daily flight frequency										
Airport	Airport									
	AMS	BCN	CDG	FCO	FRA	LHR	MAD	MUC	VIE	ZRH
AMS	0	12	14	8	11	18	11	13	10	10
BCN	12	0	10	9	6	8	63	7	4	3
CDG	14	10	0	15	18	15	13	15	9	12
FCO	8	9	13	0	7	9	11	7	4	4
FRA	11	6	18	7	0	16	12	12	14	11
LHR	18	8	15	9	16	0	13	15	8	13
MAD	10	57	13	11	12	13	0	8	2	6
MUC	13	7	15	6	12	15	8	0	12	9
VIE	10	4	9	4	14	8	2	12	0	11
ZRH	10	3	12	4	11	12	6	9	11	0

Table 3.4 - Number of passengers, declared capacity, and average delay per airport

Indicator	Airport									
	AMS	BCN	CDG	FCO	FRA	LHR	MAD	MUC	VIE	ZRH
Number of departures (pax/day)	15168	15878	16747	12511	12551	17670	16940	9670	8239	9401
Number of arrivals (pax/day)	14149	15560	15259	13327	13226	18018	18111	10294	8296	9143
Declared capacity (mov/h)	106	60	112	88	80	88	90	90	66	68

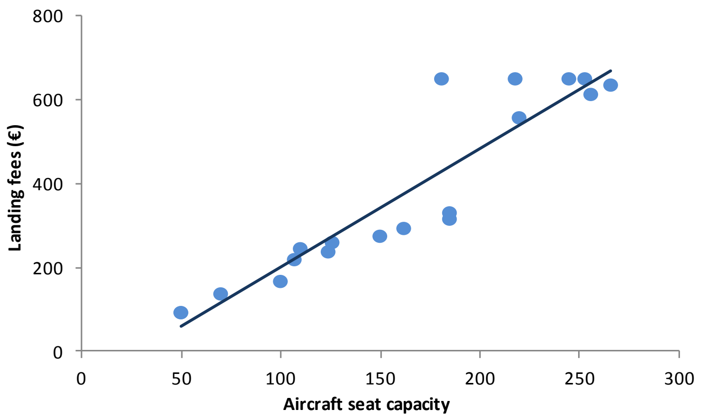

Figure 3.5 - Brussels airport landing fees as linear function of aircraft seat capacity

Passenger data per leg was collected for July 2009 using the EUROSTAT website. A daily average was calculated from the values available there and taken as the daily number of passengers per leg (Table 3.5).

Table 3.5 – Number of passengers per flight leg (July 2009)

Daily passenger demand										
Origin	Destination									
	AMS	BCN	CDG	FCO	FRA	LHR	MAD	MUC	VIE	ZRH
AMS	0	1599	1624	813	987	1836	1315	888	748	786
BCN	1474	0	1251	1007	754	1017	4375	675	387	415
CDG	1638	1326	0	2140	1608	1678	1261	1229	1045	1154
FCO	786	1005	1458	0	774	1248	1325	520	394	432
FRA	776	721	1261	793	0	1944	1453	1364	1219	772
LHR	1682	981	1605	1301	1978	0	1582	1398	800	1494
MAD	1141	3909	1491	1261	1388	1569	0	726	205	707
MUC	809	611	1089	459	1334	1360	707	0	662	437
VIE	717	400	983	408	1217	818	222	711	0	946
ZRH	896	429	1060	495	861	1207	647	512	991	0

Delay costs have two components: aircraft delay and passenger delay. For the aircraft delay costs we used the values presented in COOK and TANNER (2011) for short delays (15 minutes) and long delays (65 minutes).The average aircraft delay cost per minute is a function of aircraft seat capacity. The passenger delay cost has two parts: cost to airlines (e.g., re-bookings, compensations) and cost to passengers (time losses). The value per minute of delay was assumed to be, respectively, 0.018 EUR/pax/min and 0.75 EUR/pax/minute. Those values were obtained also from COOK and TANNER (2011), assuming a value of time of 45 EUR/hour (EUROCONTROL, 2009). Flight-leg fares were collect in a short period of time from available non-stop return fares for July 2011 without taxes and fees.

3.5.2 Study Results

The results obtained with respect to total cost, flight costs, delay costs (aircraft and passengers), flight frequencies, flights per airport, and average number of seats per leg for the optimal network and the actual network are displayed in Table 3.6. These results were obtained through the optimization model, in the case of the actual network running the model with the existing flights per airline and without considering delay costs, and calculating the delay costs afterwards to obtain the total cost.

Table 3.6 - Costs, number of flights, and passengers per flight for actual and optimal networks

Network	Total cost (M €)		Flight costs (M €)		Airport costs (M €)		Aircraft delay costs (M €)		Pax delay costs (M €)		Number of flights		Number of passengers per flight	
	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %
Actual	43.7	-	36.7	-	2.5	-	16	-	11	-	1025	-	97.0	-
Optimal	39.1	-10.4	33.1	-9.7	2.1	-16.3	0.6	-62.8	0.6	-47.2	971	-5.3	102.4	5.6

The actual network involves a total cost of 43.7 MEUR, of which 84.1 percent (36.7 MEUR) are flight costs, 5.8 percent (2.5 MEUR) are airport costs, 3.7 percent (1.6 MEUR) are aircraft delay costs, 2.6 percent (1.1 MEUR) are passenger delay, and 4.0 percent (1.7 MEUR) are schedule delay costs. The number of flights is 1,025 and the average number of passengers per flight is 97.0.

The total cost for the optimal network is 39.1 MEUR, that is, 10.4 percent smaller than for the actual network. This result is achieved with a very significant reduction of delay costs: aircraft delay costs drop by 62.8 percent and passenger delay costs by 47.2 percent. Flight and airport costs also drop, by 9.7 and 16.3 percent, to 33.1 and 2.1 MEUR, respectively. Schedule delay costs increase 54.6 percent to 2.7 MEUR. The number of flights falls to 971 (-5.3 percent), while the average number of passengers per flight increases to 102.4 (+5.6 percent).

Comparing the results per airline, it can be seen that the airlines with larger reductions in total cost are the ones with larger reductions in delay costs and number of flights: IB and LH (Table 3.7). This situation results from a substantial cut in the flight frequency of MAD-BCN (120 to 100 flights) and in the total number of flights to/from FRA and MUC, respectively. All airlines reduce their flight costs between 6.9 and 14.3 percent. The average number of passengers per flight increases between 0.7 (BA) and 8.4 percent (LH), being the smallest average number of passengers per flight 86.3 (OS) and the largest 117.4 (U2). Finally, passenger transfer between airlines is much smaller than the 5 percent limit. Indeed, only for the smallest airline considered in the case study (U2) the transfer exceeds 0.5 percent.

For the ten airports considered in the application, the total cost involved in flights and passengers departing or arriving at the airport decreases between 6.8 and 15.4 percent, and the number of flights taking-off and landing at the airport decreases between 0.5 and 9.2 percent (Table 3.8). The airport costs decrease as a result of reductions in the number of flights between 2.6 and 21.4 percent. Aircraft delay costs at the airports decrease between 58.3 percent (AMS) and 69.1 percent (MUC), and passenger delay costs decrease between 42.2 percent (AMS) and 57.7 percent (MUC). Overall, decreases in costs and number of flights are higher at FRA, MUC, BCN, and MAD, which is a direct consequence of the reduction in the number of flights for the airlines dominant in these airports (LH and IB).

Table 3.7 - Costs, number of flights, passengers, and passengers per flight per airline for actual and optimal networks

Airlines	Total cost (M €)		Flight costs (M €)		Airport costs (K€)		Delay costs (K€) Aircraft		Delay costs (K€) Passenger		Number of flights		Number of passengers		Number of passengers per flight	
	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %
AF	4.4	-10.8	3.9	-9.4	294.5	-16.3	81.8	-58.3	80.8	-52.1	120	-4.8	13146	0.1	109.5	5.1
BA	4.2	-7.8	3.7	-6.3	269.1	-6.6	106.4	-58.0	106.5	-51.4	103	-1.0	11340	-0.2	110.1	0.7
IB	5.7	-14.0	5.1	-12.4	412.5	-21.3	56.8	-65.0	50.0	-59.8	130	-9.7	13248	-0.3	101.9	10.4
KL	3.3	-7.9	3.1	-7.0	133.0	-15.2	33.5	-59.8	39.5	-51.0	103	-1.0	8978	0.3	87.2	1.3
LH	6.9	-14.3	6.4	-11.9	274.0	-18.1	143.0	-67.8	143.2	-61.5	210	-7.9	20529	-0.1	97.8	8.4
LX	2.7	-10.9	2.4	-8.2	186.8	-13.2	66.2	-64.8	65.0	-58.7	75	-3.8	8372	-0.1	111.6	3.9
OS	1.9	-9.3	1.7	-8.1	102.8	-13.6	31.3	-56.5	27.8	-50.3	52	-3.7	4485	-0.2	86.3	3.6
U2	0.3	-6.9	0.3	-5.7	26.9	-13.1	2.4	-59.3	2.5	-52.6	8	0.0	939	1.1	117.4	1.1
OTHER	7.0	-11.1	6.4	-9.8	406.1	-17.9	71.8	-62.1	73.3	-55.3	170	-5.0	18408	0.3	108.3	5.6

Table 3.8 - Costs, number of flights, and passengers per flight per airport for actual and optimal networks

Airport	Total cost (M €)		Flight costs (M €)		Airport costs (K€)		Total delay costs (K€)		Number of flights		Number of passengers per flight	
	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %
AMS	3.5	-6.8	3.3	-6.0	111.6	-17.3	43.2	-25.8	106.0	-0.5	96.7	0.5
BCN	4.3	-13.4	3.9	-12.1	362.9	-21.4	38.9	-43.9	108.0	-9.2	103.4	10.2
CDG	4.2	-12.3	3.7	-10.4	319.6	-18.3	209.4	-30.0	111.5	-7.1	111.6	7.6
FCO	3.0	-8.4	2.9	-7.7	52.1	-15.0	40.9	-33.7	71.0	-2.1	117.0	2.1
FRA	3.3	-15.4	3.0	-12.7	91.4	-10.2	215.0	-41.9	99.0	-7.5	107.1	8.1
LHR	4.8	-9.3	4.1	-7.5	357.4	-2.6	345.3	-30.2	111.5	-2.6	114.3	2.7
MAD	5.4	-12.9	4.9	-11.7	443.9	-20.4	53.9	-41.7	124.5	-8.1	101.5	8.8
MUC	2.7	-15.2	2.6	-13.3	41.8	-20.3	84.6	-48.8	91.0	-6.7	85.1	7.1
VIE	2.7	-7.9	2.4	-6.7	179.3	-13.0	41.9	-37.6	72.5	-2.0	88.7	2.1
ZRH	2.5	-9.7	2.2	-6.2	145.7	-19.5	108.7	-44.0	76.0	-3.2	93.6	3.3

3.5.3.1. Airline passenger transfer effects

The results described above for the optimal network were obtained for α=5%, thus ensuring that passenger transfer between airlines and airline market power would be small. To assess the impact of this parameter in the network, the optimization model was run using five different values of α: 0 (no passenger transfer between airlines), 10, 20, 50, and 100% (unlimited transfers). However, the results obtained for 20, 50, and 100% were the same, thus only the values for α=20% are presented. This means that allowing for a passenger variation of more than 20% does not improve the network. The main results are summarized on Table 3.9.

Table 3.9 - Costs, and number of flights for actual and optimal networks for different model alternatives

Network		Total cost (M €)		Flight costs (M €)		Airport costs (M €)		Aircraft delay costs (M €)		Number of flights	
		Value	Var %	Value	Var %	Value	Var %	Value	Var %	Number	Var %
Actual		43.7	-	36.7	-	2.5	-	2.7	-	1025	-
Optimal		39.1	-10.4	33.1	-9.7	2.1	-16.3	1.2	-56.5	971	-5.3
Optimal without delay		39.6	-9.4	33.1	-9.7	2.1	-16.3	2.5	-9.2	971	-5.3
Optimal with fixed frequency		40.6	-7.1	34.5	-5.9	2.2	-11.6	1.2	-53.9	1025	0.0
Optimal with airline passenger transfer (%)	0	39.2	-10.1	33.3	-9.4	2.1	-16.1	1.2	-56.1	975	-4.9
	10	39.0	-10.6	33.1	-9.9	2.1	-16.5	1.2	-56.7	968	-5.6
	20	38.6	-11.6	32.6	-11.1	2.1	-17.2	1.2	-57.3	951	-7.2
Optimal with passenger spill (%)	5	38.9	-11.0	33.0	-10.2	2.1	-16.8	1.1	-57.7	964	-6.0
	10	38.5	-11.9	32.6	-11.1	2.1	-17.5	1.1	-59.1	953	-7.0
	20	36.7	-16.0	30.8	-16.1	2.0	-21.3	1.0	-63.8	892	-13.0

Total cost drops with respect to the actual network by 1.2, 10.4, 10.6, and 11.6 percent for values of α of 0, 5, 10, and 20%, respectively. It can be seen that as the passenger transfers limit increases the cost savings increase but at a smaller rate. The total number of flights decreases between 4.9 percent for α=0% and 7.2 percent with α=20%. Finally, the delay costs drop 50.8 percent for α=0% and 57.3 percent for α=20%. For the number of flights and for the delay costs the rate of decrease becomes smaller with the increase in α.

The passenger transfers between airlines are always less than 2.0 percent, except for U2, even when the limit is 20 percent (Figure 3.6). For U2 the gains are: 1.1 (α=5%), 4.7

(α=10%), and 9.2 percent (α=20%). This result might be explained by the fact that U2 is the smallest of the airlines considered, and small absolute variations in the number of passengers represent high relative changes.

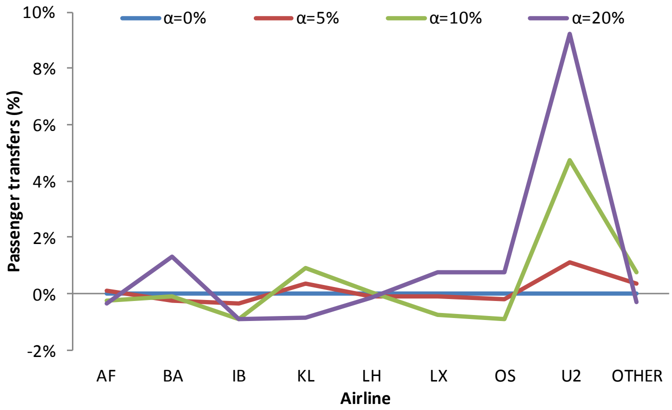

Figure 3.6 - Airline passenger variation for different airline passenger transfer limits

3.5.3.2. Delay cost effects

An important aspect of the research described in this chapter is the inclusion of aircraft and passenger delay costs in the total cost of the air transportation network. To test their influence on the final results, the model was run without considering the aircraft and passenger delay costs, and these costs were calculated afterwards to determine the total cost of the network.

The value we obtained for this cost was 39.6 MEUR, which signifies a 1.1 percent increase in relation to the optimal network (optimized with delay costs), but a 9.4 percent decrease in relation to the actual network (Table 9). The drop in costs from the actual network is due to a 9.7 percent decrease on flight costs and a 15.9 percent reduction on aircraft delay costs. In contrast, the passenger delay costs increase by 0.4 percent. The total costs increase from the optimal network is mainly due to the aircraft

(+126.0 percent) and passengers (+90.0 percent) delay costs. The number of flights and the average number of passengers per flight are the same as in the optimal network. These results indicate that flight frequency might be above the optimal in some legs as the number of flights is the same with and without delay effects, and that both aircraft and passenger delays have a significant effect in flight costs.

The results at airline and airport level are quite similar to the ones obtained for the optimal network. In relation to the actual network, the costs for airlines decrease between -7.5 and -12.2 percent, and the costs for airports decrease between -6.6 and -13.9 percent. When the comparison is made with the optimal network, as expected, all airlines and airports increase their total costs: between 0.3 and 3.2 percent for the airlines and between 0.2 and 2.9 percent for the airports.

The largest difference with respect to the optimal is in the passenger transfers between airlines (Figure 3.7). When delay costs are not taken into account, passenger transfers increase, exceeding 0.5 percent for five airlines, although continuing to be clearly less than the (5%) limit.

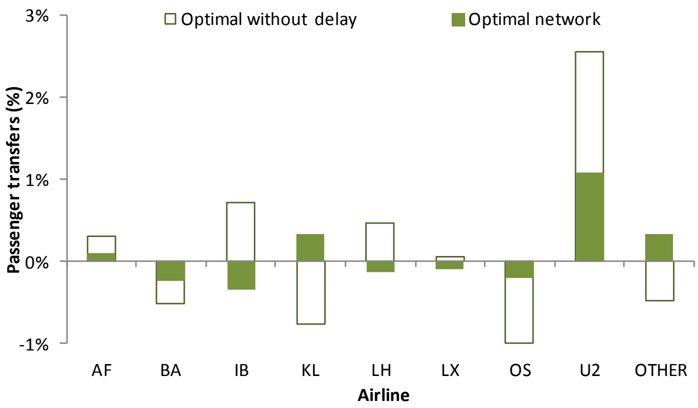

Figure 3.7 - Airline passenger variation for the optimal networks with and without delay costs

3.5.3.3. Flight frequency effect

A critical aspect for airline competition is the flight frequency per leg. As was seen before, the optimal network (obtained without fixing the flight frequency) reduces the number of flights in 5.3 percent to 971 flights, which leads to an increase in the average number of passengers per flight. Fixing the flight frequency to its actual value (1,025 flights), the total cost drops 7.1 percent in relation to the total cost of the actual network, mainly due to a 53.9 percent drop in the total delay costs (Table 9). Flight costs and airport costs also decrease 5.9 and 11.6 percent, respectively. When the comparison is made with the optimal network, total cost increases by 3.7 percent as a consequence of a generalized increase in costs, well distributed between flight, airport and delay costs.

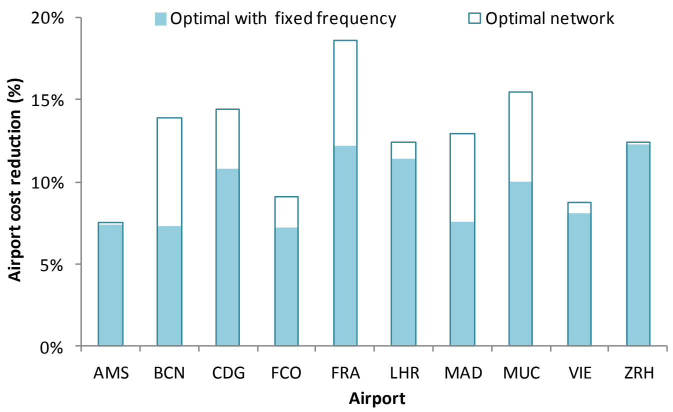

Figure 3.8 - Total cost reduction per airport for the optimal networks with variable and fixed flight frequency

At the airport level, the reduction in total costs with respect to the actual network is more evenly distributed (across airports) than the one observed for the optimal network (Figure 3.8). Largest cost decreases are mostly achieved by reducing the number of flights. This is especially true at BCN, FRA, MAD, and MUC. A similar result can be seen for the airlines: gains are smaller and better distributed than in the optimal network, though all airlines decrease its costs from the actual network.

3.5.3.4. Passenger spill effect

In the previous model alternatives, the passenger demand per leg was always fully satisfied – passengers could change airline but no passengers were spilled. Here, this assumption is relaxed by allowing passenger spill (β) up to 5%, 10%, and 20% of the actual demand per leg. In relation to the actual network, the total cost decreases between 11.0 percent (β=5%) and 16.0 percent (β=20%) which is, respectively, 0.6 percent and 4.4 percent more than in the optimal network (without passenger spill). In terms of delay costs, the drop ranges between 57.7 percent (β=5%) and 63.8 percent (β=20%), which is, respectively, 1.3 and 6.5 percent more than in the optimal network. These results seem to indicate that the cost savings are small with a passenger spill limit of 5% but tend to increase more than proportionally with the increase in the spill limit.

Total passenger spill is 3.0 (β=5%), 6.1 (β=10%), and 13.0 percent (β=20%) in relation to the actual network, corresponding to a total flight reduction of 6.0, 7.0, and 13.0 percent, respectively. In relation to the actual network, the average number of passenger per flight increases 4.0, 1.0, and 0.03 percent, respectively, for β equal to 5%, 10%, and 20%. The results at the airline and airport level are coherent with what have been seen in the previous alternatives. Passenger spill per airline is presented in Figure 3.9. Airlines (except U2) decrease the number of passengers for all values of β. The largest reductions are 3.8 percent for β=5% (BA), 8.3 percent for β=10% (AF), and 17.2 percent for β=20% (AF). At the airport level the largest decreases in terms of flights are the same as in optimal network (BCN, FRA, MUC, and MAD) plus CGD and FCO (Figure 3.10).

Figure 3.9 - Airline passenger variation for the optimal networks with different demand spill limits

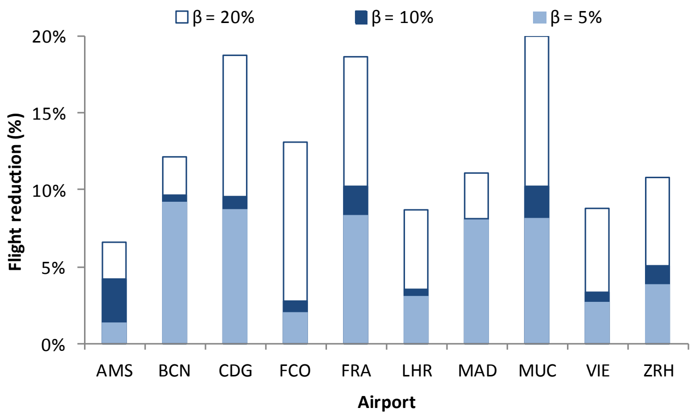

Figure 3.10 - Flight reduction per airport for the optimal networks for different demand spill limits

3.5.3 Model Solving

The model was solved on a Quad Core processor with 4GB of RAM using the commercial software Xpress with the optimizer version 22.01.04 and the Mosel version 3.2.2. (FICO, 2011). The computation time for the optimal network (α=5%) was 8.0

minutes and the linear relaxation took 1.1 seconds to solve. The computation time seems to be related with the value of α: intermediate values of α led to more time to reach optimality. Indeed, the computation time increased to 84.5 minutes when α=10% and 62.0 minutes when α=20%, and decreased to 5.5 minutes when α=0%. For α=100% the result was the same as for α=20% but the computation time was just 45.3 minutes. The 10-percent optimality gap was achieved for all α within 1 minute of computation time.

When the delay costs are not considered in the optimization model, the computation time is quite similar to when they are considered, and also depend on the value of α (varying between 3.3 and 53.8 minutes). But when the flight frequency is fixed, the optimality was reached within only one minute for all values of α (0.6 to 1.0 minutes), and when we allowed for passenger spilling the computation time varied between 1.4 (α=20%) and 6.6 (α=5%) minutes.

The computation times mentioned above are very acceptable given the type of application the model is intended to – assisting aviation authorities in their decisions regarding airport capacity usage. Moreover, the airport network considered in the application is a very dense one. This seems to indicate that the optimization model could be tractable even if the air transportation network was much larger.

3.6 Conclusions

In this chapter, we presented an approach to analyze whether, in an air transportation network, the expected passenger demand can be satisfied with the existing airport capacity at a lower total cost, including aircraft and passenger delay costs. The results obtained through its application can provide aviation authorities with valuable insights on how to improve the performance of a liberalized, congested, and slot-constrained air transportation network. The main contribution of this chapter is the optimization model underlying the approach. This model incorporates aircraft and passenger delay costs in the total costs, which is essential to understand the implications of network changes to passengers, airlines, and airports.

Analyzing the results for the case study, the first main conclusion is that costs can be significantly reduced (10.4 percent) with only minor changes in airline competition and passenger level of service. This reduction is mainly achieved by cutting by half the expected delay costs for aircraft and passenger and without demand spilling. The share of delay costs in the total costs of the system drops from around 6.5 percent to about 3 percent, even without considering delay propagation effects. The distribution of these cost savings is distributed across airlines rather evenly. Although all airports in the network reduce their costs, four of them – BCN, FRA, MAD, and MUC – gain clearly more than the others. The second conclusion is that cost reductions are obtained with a relatively small reduction in the number of flights (of around 5 percent). The flight reduction is higher for the high-frequency leg of MAD-BCN (with typically low load factors) and for flights to/from FRA and MUC, airports where LH is the clearly dominant airline. To balance this flight reduction the average number of passengers per flight should increase also around 5 percent to 6 percent. The third conclusion is that these changes can occur without significant changes in the market power of the airlines operating the network. Indeed, the results show that passenger transfer between airlines is always below 1 percent (except for the smallest airline considered in the case study). The largest airlines have higher drops in their delay costs and, therefore, in their total costs. This situation is due to the fact that these airlines have more slots to play with, being therefore capable of changing flight times to reduce their expected delays. Finally, from the airports perspective, a small change in the network design can lead to smaller costs while maintaining a good level of service for the passengers. As expected, gains are higher for the airports where delays are higher.

According to these conclusions, it seems possible to affirm that:

1. Airport capacity is sufficient to accommodate the existing demand (or even an increase in demand) if airports and airlines agree to small changes in the actual network design.
2. Airline profitability is not compromised by a reduction of flight frequencies, as delay costs drop more than proportionally with the decrease in these frequencies.
3. Airlines can reduce delay costs if they change their flights in order to avoid flying between peak periods at the departure and arrival airports, or at least avoiding the peak period at one of the airports.
4. Passengers will not see a deterioration of their level of service because flight frequency reduction is small, they can still travel close to their desired travel time, and their expected delay time is significantly reduced.

The conclusions stated above were drawn relying on a number of simplifications. In particular, they involve origin-destination demand (and leg-interdependence) effects and delay propagation effects. Also, airline market share was dealt with in a simplified way, assuming that an airline will have a demand share per leg and time period proportional to their seat share. Despite these simplifications, we believe that the insights provided through the optimization model can be very useful for aviation authorities, airlines and airports in their discussions regarding a better usage of airport capacity.

Chapter 4

Integrated Flight Scheduling and Flight Assignment under Airport Congestion

4.1 Introduction

The liberalization of air transport markets and its consequences, such as the increase in traffic, have led airlines to a large number of functional changes. One of the most important is the adoption by airlines of hub-and-spoke networks. Other changes are the reduction of the average price per available seat-kilometer, the rise in flight frequencies, and the establishment of partnerships between airlines (BELOBABA et al., 2009). A negative consequence of the growth in air traffic for airlines and passengers is the increase in airport congestion and flight delays. This signifies huge costs to the airlines and the economy – according to a recent report, the total delay costs for the US economy in 2007 were USD 32.9 billion, including USD 16.7 billion of direct costs to passengers and USD 8.3 billion of direct costs to airlines (NEXTOR, 2010).

Airlines can address the challenges they face in this context in a multiplicity of ways. In particular, it is crucial that they make an optimal choice of the timetable for the flights they offer in each market – flight scheduling – and of the aircraft they use for each flight – fleet assignment.

Flight scheduling and fleet assignment are fundamental stages of the airline planning process. Models that deal with both issues simultaneously led to significant improvements in airlines that operate in competitive markets (REXING et al., 2000; LOHATEPANONT and BARNHART, 2004). These models assume that the schedule will be met as planned (AHMADBEYGI et al., 2008), something that does not happen in many occasions. Therefore, they disregard important costs currently faced by airlines.

In this chapter, is presented a mixed-integer linear optimization model for integrated flight scheduling and fleet assignment where the costs for an airline associated with aircraft and passenger delays are explicitly taken into account. The objective of the model is to maximize the expected profits of the airline for a given O/D-based (or itinerary-based) travel demand. The model is designed for application to networks that include some congested, slot-constrained airports, considering in a simplified manner both airline competition and airline cooperation (alliances, partnerships). The usefulness of the model is demonstrated through a case study involving the main network of TAP Portugal.

Flight delays and their implications have been extensively debated in the literature, from a wide variety of standpoints – including flight scheduling. In this context, basically two types of model have been proposed: schedule recovery models, which are applied during operations to return a disrupted schedule to the plan (BRATU and BARNHART, 2006); and robust scheduling models, which are used to create new flight schedules by re-timing and re-fleeting existing schedules to reduce expected operating costs and increase schedule robustness (LAN et al., 2006). The model proposed here can be classified in the latter type, but differs from the existing models in several respects – and particularly because delay costs are dealt with in an O/D-based flight scheduling and fleet assignment framework.

The chapter is organized as follows. After this introduction, is presented an overview of the flight scheduling and fleet assignment literature. Next, is provided a detailed explanation of the ingredients of integrated flight scheduling and fleet assignment problems, where the implications of airport congestion, airline competition, and airline cooperation are examined. Then, is formulated the mixed-integer linear optimization model, specify the assumptions upon which the model is based, and describe its application to the TAP network. In the final section is appraised the strengths and limitations of the model, and identify directions for future research.

4.2 Literature Overview

Flight scheduling and fleet assignment are two very important (and difficult) stages of the airline planning process, and have motivated a great deal of attention in the air transport literature (BARNHART et al., 2003; CLARK and SMITH, 2004). In general, these stages have been dealt with separately until the 1990s due to computational limitations, but, since then, there have been significant efforts to partially or fully integrate them.

Flight scheduling is the process through which airlines decide the timetable of their flights with the typical objective of maximizing profits. The first flight scheduling models date back to the 1960s and 1970s. Work carried out in this period is thoroughly reviewed in ETSCHMAIER and MATHAISEL (1985). In the last two decades, great progress has been made by re-timing, changing, adding, or removing flight legs from an existing schedule – see e.g. BERGE and HOPPERSTAD (1993) and LOHATEPANONT and BANHART (2004) – or by building schedules from scratch to charter airlines – see e.g. ERDMANN et al. (2001) and BARNHART and KIM (2005). All these models deal with a single airline. Recently, YAN and CHEN (2007) presented a flight scheduling model for airline alliances, claiming that it was successfully applied to two Taiwan airlines.

Fleet assignment is the process through which airlines assign aircraft to flights with the typical objective of minimizing costs. Fleet assignment problems (FAP) were first tackled in FERGUSON and DANTZIG (1955), that is, even before flight scheduling problems started to be addressed from an optimization perspective. The literature on these problems has been recently reviewed by SHERALI et al. (2006). The two core models are the ones presented in ABARA (1989) and HANE et al. (1995). The former set the usual constraints of a FAP model – cover, balance, aircraft availability, and schedule balance constraints – and uses all feasible connecting arcs between flights as decision variables. RUSHMEIER and KONTOGIORGIS (1997) increased the efficiency of ABARA's formulation by explicitly considering the possible connections, and developed a heuristic algorithm to solve the model. In HANE et al. (1995) the fleet type to fly each flight leg is used as a decision variable of the model, thus reducing the number of variables. Also, it introduced other widely-used techniques – node consolidation and island construction – to further reduce the size of the model. The previous models use leg-based information, therefore they do not take connecting passengers and hub-and-spoke network effects into account. O/D-based FAP models were proposed by JACOBS et al. (1999) and BARNHART et al. (2002). In these models, demand, recapture, and fares are all considered at the origin-destination market level and not per leg, which leads to more meaningful results. It has been shown that their application can result in significant additional profits to airlines.

Solving flight scheduling and fleet assignment models sequentially may lead to sub-optimal results. To avoid this, the two airline planning stages must be dealt with in an integrated manner. In this case, airlines decide simultaneously the timetable of their flights and the aircraft to assign to each flight. LEVIN (1971) was the first to propose a (very simple) integrated model, considering a single aircraft type and discrete flight time windows. The same approach was adopted in models proposed by DESAULNIERS et al. (1997) and REXING et al. (2000). Both define a set of possible re-timing arcs for each flight leg and allow for a heterogeneous fleet. The models pick the re-timing arcs that optimize airline profits. It is assumed that the flight legs are known, which means that a base-schedule has to exist (or be built) previously. LOHATEPANONT and BARNHART (2004) relaxed the assumption of fixed and known flight legs. They start by dividing the flights in two sets: mandatory and optional. The optimization process then chooses the optional flights that maximize airline profits while taking into account the impact of flight frequency on travel demand. Airline competition is considered in the demand function through a quality of service index. This work was recently extended to stochastic travel demand conditions by YAN et al. (2008).

None of the integrated models referred to above address flight delay issues. But these issues are dealt with in two types of optimization models: schedule recovery models and robust scheduling models. In schedule recovery models (ROSENBERGER et al., 2001a; BRATU and BARNHART, 2006) the objective is to optimize the aircraft and/or passenger routing after the occurrence of an unexpected event. These are reactive models because they are applicable only after the disruption has taken place. In robust scheduling models (ROSENBERGER et al., 2001b; LAN et al., 2006; GAO et al. 2009), the objective is to minimize the cost of delays (or a surrogate variable) by introducing slackness, or other attributes providing flexibility to recover, in the airline schedule.

The model presented in this chapter is of the latter type. However, unlike the models currently available, it is not based on a pre-defined schedule – the schedule is established as a function of the expected aircraft and passenger delays in an integrated O/D-based flight scheduling and fleet assignment framework, considering both airline competition and airline cooperation issues. Taken together, these features make our model a significant contribution to the airline planning literature.

4.3 Problem Ingredients

The problems faced by airlines when they make their flight scheduling and fleet assignment decisions are highly complex, particularly when the airlines operate in congested, slot-constrained airports. .Below, we detail a number of ingredients that should be contemplated in a model developed for assisting airlines at making those decisions.

In many airports, particularly in Europe, airlines are limited in the number of slots they can use because the declared capacity of airports is insufficient to accommodate peak period demand, constraining the choices of airlines in terms of time and frequency of flights (ACL, 2009). The allocation of airport slots to airlines is decided during the IATA scheduling conferences (IATA, 2008a). These conferences are held every six months to provide a forum for the allocation of slots and for the reaching of consensus on the schedule adjustments necessary to conform to airport capacity limitations. A significant part of the slots is assigned through the mechanism of grandfather rights, being kept by the same airlines from season to season (BARBOT, 2004). The remaining slots are assigned taken into account the scheduling needs of airlines. Thus, on the one hand, schedules are set given the available slots and, on the other hand, slots are requested to meet scheduling needs.

The requests for slots, as well as the average number of seats per flight, are related to the competition between airlines. In liberalized markets there is a higher frequency of flights and a lower number of seats per flight (GIVONI and RIETVELD, 2009). Airlines tend to increase their frequencies both by adding new non-stop flights and by offering connecting itineraries. Airlines do that to gain market share, since there is a positive (empirical) relationship between the number of passengers that an airline can expect to serve and the frequency of flights they offer in a market. The relationship is often considered to have the shape of an S-curve, particularly in short and medium-haul markets (SIMPSON, 1970; BELOBABA et al., 2009).

The passenger demand per market is forecast through specialized models (WEI and HANSEN, 2005). In each market, there are passengers desiring distinct kinds of service: some want to travel non-stop while others are more price-sensitive and prefer to take a connecting itinerary with reduced price. The relative portion of passengers willing to fly non-stop is a function of the type of market (business or leisure), distance, flight frequency, and competition (VASIGH, et al., 2008). With appropriate quality share indexes (QSI), airlines can estimate the percentage of passengers that will pay for non-stop premium service, and then select itineraries and frequencies to match that demand.

The price-sensitive passengers may accept to fly in connecting itineraries, particularly if they involve only one stop (COLDREN et al., 2003). Each connecting itinerary offered by an airline uses one or more of its hubs as connecting points. But airlines can also use the flights of partner airlines to increase the number of connecting itineraries they make available to passengers (ABEYRATNE, 2000; FAN et al., 2001). In BRUECKNER (2003) it is shown that both code-sharing and anti-trust immunities reduce the fares for passengers on international flights by around 10%. This allows airlines to increase the market share on the flight legs they offer provided that a good level of schedule coordination among airlines is assured (WAN et al., 2009). In particular, it is necessary to guarantee that the connecting time is properly sized. Otherwise, if the connecting time is too long the attractiveness of the itinerary will decrease, and if it is too short it can lead to misconnections with significant flight delays and large costs to airlines.

Data from the US domestic network in 2007 show that disrupted passengers experience "an average delay of 456 minutes accounting for 50% of all passenger delay minutes, but are only 3.4% of the delayed passengers" (NEXTOR, 2010). This means that each passenger that misses a connection has a much higher cost for an airline than a passenger that is delayed but still manages to get her/his flight. Thus, reducing the probability of passenger disruption will have a strong impact on delay costs. It should be underlined here that aircraft delays can be substantially different from passenger delays when passengers are traveling in connecting itineraries (LAN et al., 2006). Occurrence of delays is especially likely to happen in airports characterized with a utilization rate of 85% or more (above that rate delays increase sharply, see DE NEUFVILLE and ODONI, 2003).

Airlines must make their flight scheduling and fleet assignment decisions taking all these aspects into account, as well as the costs and revenues they can make in each market. Revenues are essentially made from selling tickets, with the fares applied to non-stop trips being typically higher than those applied to connecting trips (which are made by the most price-sensitive passengers). Costs can be divided into four categories: vehicle costs, airport costs, spill costs, and passenger delay costs. Vehicle costs consist mainly of fuel, crew, maintenance, leasing, and aircraft depreciation costs, as well as navigation taxes. Airport costs are the landing fees and other airport charges paid by airlines to airport authorities. Together, vehicle and airport costs signify more than 60 percent of the total costs of an airline (SWAN and ADLER, 2006). Part of these costs is attributable to aircraft delays. Spill costs are the losses in airline revenues resulting from insufficient seating capacity to satisfy demand. Finally, passenger delay costs are the costs to the airline of passengers that miss their connection due to delays in a previous flight leg. These costs include re-accommodation costs and costs associated with a loss of good will.

4.4 Optimization Model

In this section is described the formulation of the optimization model designed to represent the integrated flight scheduling and fleet assignment problem faced by an airline that operates mainly in slot-constrained airports, as well as the assumptions upon which the model is based. The objective of the airline is to maximize (expected) profits while satisfying the demand for its flights, taking into account airport congestion (arrival delays), airline competition, and airline collaboration issues. The model applies to a given network of non-stop and one-stop flights, and a given planning period (e.g. one day or one week), being each day divided into demand periods (e.g. early morning, late morning, early afternoon, etc.), and each demand period further divided into slot time windows (of, say, 15 minutes).

4.4.1 Model Assumptions

The optimization model relies on the following assumptions:

(1) The markets served by the airline, the network structure (hubs), the available fleet, the unit revenues for non-stop and (one-stop) connecting flights, the unit vehicle, airport, spill, and delay costs, and the arrival delays distribution at the airports are known (or can be anticipated with reasonable accuracy).

These assumptions reflect the fact that flight scheduling decisions have a short-term nature – they are made approximately one year in advance of the season to which they apply.

(2) The flight frequencies of airline's competitors are known (or can be anticipated with reasonable accuracy).

This assumption is plausible if decisions are being made during the IATA scheduling conferences, as information about slot requests becomes available. Even before the conferences, it is also plausible in situations where, like in Europe, airports are slot-constrained. In this case, flight frequencies are quite difficult to change, as airlines need to find vacant, compatible slots both in the departing and the arrival airport.

(3) The market share of the airline can be expressed as a piecewise linear function of flight frequency.

The market share of an airline in a given market is the ratio between its flight frequency in that market and the total flight frequency in the market. For each demand period, it can be expressed as follows:

$$M_{jkp} = \frac{Fr_{jkp}^{\mu}}{\sum_{b \in \boldsymbol{B}} Fr_{bjkp}^{\mu}} \quad (4.1)$$

where $\boldsymbol{B} = \{1, \ldots, B\}$ - set of airlines that operate in the market; M_{jkp} - share of the airline in market *jk* in demand period *p; Fr_{jkp}* - frequency of the airline in market *jk* in demand period *p*; μ - parameter greater than 1 representing the impact of flight frequency on market share (for larger μ the impact is larger); Fr_{bjkp} - frequency of airline *b* in market *jk* in demand period *p*.

If the flight frequencies of the other airlines in the market are known, which is in line with assumption (2), the relationship between market share and flight frequency represented with expression (4.1) can be plotted as an S-curve (Figure 4.1). Such curve can be approximated by a piecewise linear function with as much accuracy as the number of pieces of the function.

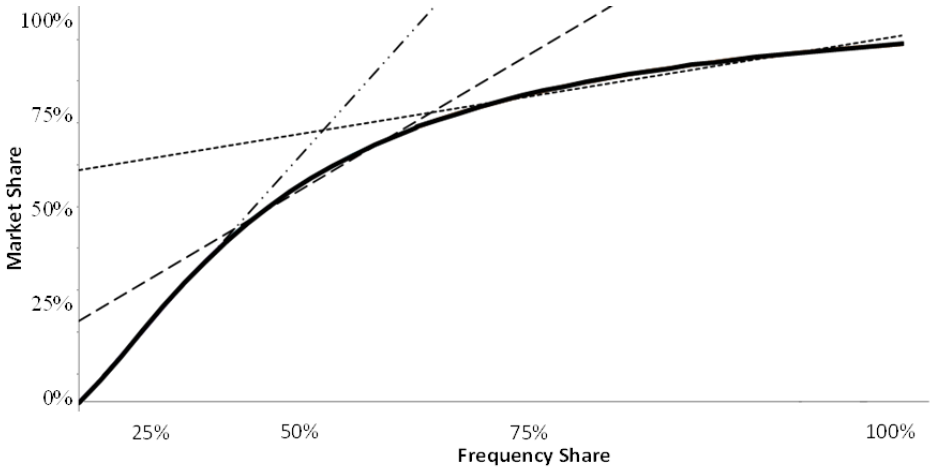

Figure 4.1- Piecewise linear approximation of the S-curve

(4) The effect of slight changes in passenger connecting time upon the demand faced by the airline is negligible.

Travel costs, which include ticket fares and time costs, are an essential determinant of travel demand. Time costs include in-flight time and connecting time costs. If the increase in connecting times is small as compared to total travel time, the decrease in travel demand would be minor. Moreover, such decrease would be at least partly compensated with the increase in travel demand that would in principle arise from the decrease of the probability of passengers being disrupted. Hence, travel demand should remain almost unchanged as a consequence of slight changes in connecting times.

(5) The recapture rate of the airline for a given market is a function of travel time and current market share.

The recapture rate of an airline is the fraction of demand spilled in a given period that is regained by the airline in later periods. Estimation of recapture rates is a complex task, mostly dealt with in the revenue management field (COLDREN and KOPPELMAN, 2005; RATLIFF et al., 2008; GALLEGO et al., 2010). To our best knowledge, the only airline operational planning models where passenger recapture is taken into account are the ones presented in BARNHART et al. (2002) and LOHATEPANONT and BARNHART (2004). In these articles a quality share index (QSI) is used to estimate recapture rates. The QSI measures the attractiveness of an itinerary, and is related with the airline's market share.

The expression that will be used in the computation of recapture rates is as follows:

$$\alpha_{jkp} = \max\left[0\ ;\ M^{0}_{jkp} \times \left(1 - \frac{1}{t_{jk}}\right)\right], \forall j,k \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{4.2}$$

where α_{jkp} - recapture rate for market jk in demand period p; M^{0}_{jkp} is the current airline market share in demand period; and t_{jk} - travel time without delay between airports j and k.

Expression (4.2) makes the recapture rate of the airline for a given market dependent on travel time (if this time is smaller than one hour then no passengers are recaptured) and (current) market share; that is, it captures two important aspects influencing the attractiveness of an itinerary – and the QSI. Indeed, it is expected that long-haul markets are less sensitive to departure/arrival time than short-haul markets (JORGE-CALDERÓN, 1997). Also, if an airline has a large market share, it should be able to recapture a large fraction of demand.

In the previous expression, current market share is used as an indicator of actual market share. This certainly is a simplification, but its consequences should be acceptable if the airline flight frequencies (and market shares) do not change substantially, which is likely to be the case if the current flight schedules fit well the demand faced by the airline. The simplification is important because it allows to keep the optimization model linear while taking recapture rates into account (as shown in BARNHART et al., 2002, "the benefit of incorporating recapture into the fleeting decision process outweighs any errors that might result from inaccurate recapture rates").

(6) The airline can assign passengers to partner flights in one of the legs of a connecting itinerary.

This assumption reflects one of the main facets of airline collaboration. By assigning passengers to partner flights in one of the legs of a connecting itinerary, airlines provide service in markets that otherwise they would not be able to serve. The revenues are then split across the airlines involved, typically in proportion with the length of the legs.

4.4.2 Model Formulation

For formulating the model, consider the following additional notation:

Sets: $\boldsymbol{A} = \{1, \ldots, A\}$ - set of airports; $\boldsymbol{A_0} = \{1, \ldots, A_0\}$ - set of hub airports; $\boldsymbol{P} = \{1, \ldots, P\}$ - set of demand periods; $\boldsymbol{T} = \{1, \ldots, T\}$ - set of slot time windows; $\boldsymbol{T_P} = \{1, \ldots, T_P\}$ - set of slot time windows belonging to each demand period p; $\boldsymbol{F} = \{1, \ldots,$

$F\}$ - set of aircraft types.

Parameters: r^N_{jk} - revenue for non-stop flights in market jk (USD per passenger); r^C_{jk} - revenue for connecting flights in market jk (USD per passenger); c_{Vjkf} - vehicle cost for an aircraft of type f on leg jk if the flight is not delayed (USD per flight); c_{Ajf} - airport cost for an aircraft of type f at airport j if the flight is not delayed (USD per flight); α^N_{jkp} - recapture rate in market jk for demand period p on non-stop flights for the current market share; α^C_{jkp} - recapture rate in market jk for demand period p on connecting flights for the current market share; c_{Df} - delay cost for an aircraft of type f (USD per slot time window); $p_{jt,t'-t}$ - probability of a flight set to arrive at airport j in slot time window t being delayed more than $(t'-t)$ slot time windows; $c_T{}^{MIN}{}_j$ - minimum connecting time for passengers at airport j (measured in slot time windows); c_{Pjk} - average cost per slot time window for a disrupted passenger travelling on market jk (USD per passenger and slot time window); s_{jt} - available slots at airport j in slot time window t; n_f - number of aircraft of type f; d^N_{jkp} - passenger demand for non-stop flights in market jk and demand period p; d^C_{jkp} - passenger demand for connecting flights in market jk and demand period p; a_{jkp} - slope of the piecewise linear approximation of the S-curve corresponding to market jk in demand period p; β - parameter smaller than 1 representing the relative loss of utility of a connecting flight (Simpson, 1970; Belobaba et al., 2009); b_{jkp} - intercept of the piecewise linear approximation of the S-curve corresponding to market jk in demand period p; s_{Vf} - capacity of an aircraft of type f.

Decision Variables: q^N_{jkt} - number of passengers that fly non-stop between airports j and k taking off in slot time window t; q^{C1}_{jhkt} - number of passengers on itinerary j-h-k that fly from airport j to hub h taking off from j in slot time window t; q^{C2}_{jhkt} - number of passengers on itinerary *j-h-k* that fly from hub *h* to airport *k* taking off from *h* in slot time window *t*; x_{jkft} - number of flights by aircraft type *f* on leg *jk* that take off in slot time window *t;* z^N_{jkp} - number of passengers spilled from non-stop flights in market *jk* in demand period *p;* z^C_{jkp} - number of passengers spilled from connecting flights in market *jk* in demand period *p;* $w_{jhktt'}$ - number of connecting passengers that are waiting at airport *h* on itinerary *j-h-k* that are set to arrive at airport *h* in slot time period *t* and depart from airport *h* in slot time window *t'*; y_{jft} - number of aircraft of type *f* that are available to take off from airport *j* in slot time window *t.*

Using this notation, the objective-function of the model can be formulated as follows:

$$\begin{aligned}
\max \Pi = & \sum_{j,k\in \boldsymbol{A}} \sum_{t\in \boldsymbol{T}} r^N_{jk} \times q^N_{jkt} + \sum_{j,h,k\in \boldsymbol{A}} \sum_{t\in \boldsymbol{T}} r^C_{jk} \times q^{C1}_{jhkt} \\
& - \sum_{j,k\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} \sum_{t\in \boldsymbol{T}} \left(c_{Vjkf} \times x_{jkft} + c_{Ajf} \times x_{kjft} \right) \\
& - \sum_{j,k\in \boldsymbol{A}} \sum_{p\in \boldsymbol{P}} r^N_{jk} \times \left(1-\alpha^N_{jkp}\right) z^N_{jkp} - \sum_{j,h,k\in \boldsymbol{A}} \sum_{p\in \boldsymbol{P}} r^C_{jk} \times \left(1-\alpha^C_{jkp}\right) z^C_{jhkp} \\
& - \sum_{j,k\in \boldsymbol{A}} \sum_{f\in \boldsymbol{F}} \sum_{t'\in \boldsymbol{T}\therefore t'>t} \sum_{t\in \boldsymbol{T}} c_{Df} \times p_{jt,t'-t}\left(t'-t\right) \times x_{kjft} \\
& - \sum_{j,h,k\in \boldsymbol{A}} \sum_{t'\in \boldsymbol{T}\therefore t'>t+c_{T\,j}^{MIN}} \sum_{t\in \boldsymbol{T}} c_{Pjk} \times w_{jhktt'} \times p_{jt,t'-t-c_{T\,j}^{MIN}} \left(t'-t-c_{T\,j}^{MIN}\right)
\end{aligned} \qquad (4.3)$$

Function (4.3) expresses the maximization of the (expected) profits of the airline. The first two terms represent revenues associated with non-stop and connecting itineraries, respectively. The next term represents vehicle costs and airport costs. The fourth and fifth terms capture spill costs for non-stop and connecting passengers, respectively. The spill costs are calculated assuming that a fraction of the demand that cannot be met in a given period will be transferred to a different demand period, according to a given recapture rate. The aircraft delay costs (sixth term of the objective function) are calculated by multiplying the unit cost of a delayed aircraft with the expected flight delay. The passenger delay costs, last term of objective function, are calculated by multiplying the number of passengers affected by the delay and the unit cost per slot time window of a disrupted passenger by the probability of a passenger being delayed and left with insufficient time to make the connecting flight.

The objective-function is to be optimized considering the following constraints:

$$\sum_{k\in \boldsymbol{A}}\sum_{f\in \boldsymbol{F}}\left(x_{jkft}+x_{kjft-t_{kj}}\right)\leq s_{jt}\ ,\ \forall j\in \boldsymbol{A},t\in \boldsymbol{T} \tag{4.4}$$

$$\sum_{k\in \boldsymbol{A}}\sum_{t\in \boldsymbol{T}}\left(x_{jkft}-x_{kjft}\right)=0,\ \forall j\in \boldsymbol{A},f\in \boldsymbol{F} \tag{4.5}$$

$$\sum_{j\in \boldsymbol{A}}y_{jft}+\sum_{j,k\in \boldsymbol{A}}x_{jkft}+\sum_{j,k\in \boldsymbol{A}}\ \sum_{b\in \boldsymbol{T}\therefore u<t,u+t_{jk}>t}x_{jkfu}=n_f\ ,\ \forall f\in \boldsymbol{F},t\in \boldsymbol{T} \tag{4.6}$$

$$\sum_{k\in \boldsymbol{A}}x_{jkft}\leq\sum_{k\in \boldsymbol{A}}x_{kjft-t_{kj}}+y_{jf,t-1},\ \forall j\in \boldsymbol{A},\ f\in \boldsymbol{F},t\in \boldsymbol{T}:t>1 \tag{4.7}$$

$$\sum_{k\in \boldsymbol{A}}x_{jkf1}\leq y_{jfT}+\sum_{k\in \boldsymbol{A}}x_{kjft^{MAX}-t_{kj}},\ \forall j\in \boldsymbol{A},\ f\in \boldsymbol{F} \tag{4.8}$$

$$d_{jkp}^{N}\times M_{jkp}+\alpha_{jkp}^{N}\times z_{jk,p-1}^{N}-z_{jkp}^{N}=\sum_{t\in \boldsymbol{T_P}}q_{jkt}^{N}\ ,\forall j,k\in \boldsymbol{A},p\in \boldsymbol{P} \tag{4.9}$$

$$d_{jkp}^{C}\times M_{jkp}+\alpha_{jkp}^{C}\times z_{jk,p-1}^{C}-z_{jkp}^{C}=\sum_{h\in \boldsymbol{A}}\sum_{t\in \boldsymbol{T_P}}q_{jhkt}^{C1}+\sum_{h\notin \boldsymbol{A_o}}\sum_{t\in \boldsymbol{T_P}}q_{jhkt}^{C2}\ ,\ \forall j,k\in \boldsymbol{A},p\in \boldsymbol{P} \tag{4.10}$$

$$M_{jkp}=a_{jkp}\left(\sum_{f\in \boldsymbol{F}}\sum_{t\in \boldsymbol{T_P}}x_{jkft}+\beta\sum_{h\in \boldsymbol{A}}\sum_{f\in \boldsymbol{F}}\sum_{t'\in \boldsymbol{T}:t'>t(x_{jhft}>0)+t_{jh}}x_{hkft'}\right)+b_{jkp},\forall j,k\in \boldsymbol{A},\ p\in \boldsymbol{P} \tag{4.11}$$

$$q^{C2}_{jhkt} \leq \sum_{t' \in \boldsymbol{T} \therefore t' < t + t_{jh}} q^{C1}_{jhkt'} - \sum_{t'' \in \boldsymbol{T} \therefore t'' < t} q^{C2}_{jhkt''}, \forall j,k \in \boldsymbol{A}, h \in \boldsymbol{A_0}, t \in \boldsymbol{T} \tag{4.12}$$

$$\sum_{f \in \boldsymbol{F}} x_{jkft} \times s_{V\,f} \geq \sum_{h \in \boldsymbol{A}} (q^{C1}_{jkht} + q^{C2}_{hjkt}) + q^{N}_{jkt}, \forall j,k \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{4.13}$$

$$\sum_{t' \in \boldsymbol{T} \therefore t' < t - c_{T_j}^{MIN}} w_{jhkt't} = q^{C2}_{jhkt}, \forall j,h,k \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{4.14}$$

$$\sum_{t' \in \boldsymbol{T} \therefore t' > t + c_{T_j}^{MIN}} w_{jhktt'} = q^{C1}_{jhkt}, \forall j,h,k \in \boldsymbol{A}, t \in \boldsymbol{T} \tag{4.15}$$

$$x_{jkft} \in \{0,1\}, \forall j,k \in A, f \in \boldsymbol{F}, t \in \boldsymbol{T} \tag{4.16}$$

$$q^{N}_{jkt}, q^{C1}_{jhkt}, q^{C2}_{jhkt}, w_{jhktt'}, y_{jft} \geq 0, \forall j,h,k \in \boldsymbol{A}, t,t' \in \boldsymbol{T} \tag{4.17}$$

$$z^{N}_{jkp}, z^{C}_{jkp} \geq 0, \forall j,k \in \boldsymbol{A}, p \in \boldsymbol{P} \tag{4.18}$$

The role of these constraints is as follows. Capacity constraints (4.4) restrict the use of an airport for departures and arrivals to the slots available. Balance constraints (4.5) ensure that during the planning period the number of take-offs is equal to the number of landings per aircraft type and airport. Availability constraints (4.6) limit the use of aircraft to the existing fleet. Continuity constraints (4.7) and (4.8) guarantee aircraft continuity in each airport, for each time period and aircraft type. Demand equations for non-stop passengers (4.9) specify whether the demand for each market is either satisfied or spilled. The non-stop demand in a given demand period is the number of passengers willing to travel in the period multiplied by the airline market share plus the passengers that are recaptured from the previous period. Constraints (4.10) play a similar role for connecting passengers, while taking into account whether both legs are flown by the airline or one of them is flown by a partner airline. Constraints (4.11) express the market share of the airline as a piecewise linear function of flight frequency. Constraints (4.12) ensure that, in connecting itineraries with both legs flown by the airline, the passengers in the first leg also make the second leg. Constraints (4.13) guarantee that the number of seats in each flight must be higher than the number of passengers assigned to the flight. Constraints (4.14) and (4.15) define the waiting passengers in each itinerary *j-h-k* and their connecting time. Constraints (4.14) force that the sum of the waiting passengers in a market *j-h-k* that arrive at airport *h* on time window *t'* and depart on time window *t* is equal to the passengers in itinerary *j-h-k* that depart from airport *h* on time window *t*. Analogous constraints (4.15) are included for passengers on the first leg of a connecting itinerary. Finally, expressions (4.16) to (4.18) define the domain of the decision variables.

4.5 Case study

The optimization model presented in the previous section was applied to a case study involving the main network of TAP Portugal, the Portuguese legacy carrier. This airline operates mainly in Europe, in Portuguese-speaking countries of Africa (particularly, Angola and Mozambique), and in Brazil. TAP main network consists of the 31 airports served non-stop with a minimum of 7 flights per week in the 2009 IATA summer season, 100 daily flight legs and more than 300 O/D markets (Figure 4.2). TAP's network is based on a major hub in Lisbon (LIS) and a minor hub in Porto (OPO).

The study consisted in determining the optimal flight schedule and fleet assignment solutions for TAP's main network, and comparing them with the current situation. The solutions were obtained considering the following modeling alternatives:

- Market shares do not change with flight frequencies vs. market shares vary with flight frequencies according to the piecewise linear approximation of the S-curve. The former alternative is designated as "fixed market shares" and the latter as "variable market shares".

- Slots currently used by the airline must remain the same vs. slots can change freely within an interval of one hour centered in the initial slots. The former alternative is designated as "fixed slots" and the latter as "variable slots".

- Delay costs are taken into account in the optimization model vs. delay costs are not taken into account (they are calculated after solving the model).

The comparison of solutions was made considering the following indicators: airline profits, total number of flights, delay costs, average passenger connecting time, and average number of feasible connections per flight.

Below, we start by providing information on the data used in the study and on model solving issues. Then, we present the results we have obtained for a week of operations, for the busiest day of the week, and an analysis of the sensitivity of results to changes in some key parameters.

It should be underlined here that this is an academic study, where a real-world network is used to exemplify the kind of results that are possible to obtain with the optimization model.

Figure 4.2 - Main network of TAP Portugal in the IATA Summer Season 2009

4.5.1 Study Data

The data used in the application was: number of slots used by TAP in the 2009 IATA summer season, number of weekly flights per leg, set of partner flights and their schedules, set of competitor flights and their schedules, arrival delays distribution for each airport, demand per market and type of service (non-stop vs. connecting), operating costs per leg and aircraft type, and average fares per market and type of flight. These data were provided by TAP or taken from EUROCONTROL reports.

The number of slots used by TAP varies with the day of the week, with the weekly total being 3,236 slots. The busiest day of the week is Friday, with a total of 480 slots. Lisbon is the airport with the largest number of slots – around 200 per day. A sample of the TAP schedule (from which we took the slots available per airport) is shown in Table 4.1.

Table 4.1 - TAP flights in the IATA Summer Season 2009 (sample)

Route	Departure	Arrival	Day						
			MO	TU	WE	TH	FR	SA	SU
EWR-OPO	00:05	07:15		X			X	X	
GIG-LIS	01:50	11:25		X	X		X	X	X
LIS-GIG	08:35	18:50	X	X	X	X	X	X	X
OPO-GRU	09:15	20:05		X		X		X	
OPO-EWR	10:25	18:30	X			X	X		
LIS-EWR	10:35	19:05	X	X	X	X	X	X	X
GRU-OPO	21:35	07:45		X		X		X	
EWR-LIS	22:15	05:30	X	X	X	X	X	X	X

The number of weekly flights in TAP's main network is 1,618 (50% of the total number of slots). The daily distribution of the flights and the minimum fleet necessary to fly them are displayed in Table 4.2. The minimum fleet was calculated taking into account the average turn time values of 45 minutes for narrow-body aircraft and 90 minutes for wide-body aircraft.

Table 4.2- Number of TAP daily flights and minimum fleet per week day

Day		MO	TU	WE	TH	FR	SA	SU
Number of flights		229	230	229	234	240	227	229
Aircraft type	ER4	7	6	6	6	7	6	7
	F 100	4	4	3	5	4	5	4
	A - 319	14	13	14	13	13	14	12
	A - 320	8	9	10	9	9	6	9
	A - 321	3	2	3	2	3	1	3
	WIDE	5	5	5	6	6	5	5

The set of partner flights consists mainly of flights offered by the airlines of Star Alliance (of which TAP is a member) but also includes flights involving specific bilateral agreements (e.g. some Iberia flights to/from Brazil). The schedule of those flights was assumed to be fixed and operated without delays. Passengers can be assigned to these flights if the scheduled arrival and departure allow at least the minimum connecting time of 30 minutes. An example of the available partner flights to Munich is shown in Table 4.3. The set of competitor flights consists of all flights offered by airlines other than TAP for the markets considered.

Table 4.3 - Available flights to Munich from partner airlines

Partner flight to Munich	
Departure airport	Departure time
BCN	12:05
MAD	12:30
BRU	12:40
FRA	13:05
MXP	13:10
ZRH	13:30
MAD	15:30
LUX	17:10
BCN	18:05
ZRH	19:05
ZRH	20:45
FRA	21:25

With the schedules of TAP and competitors, the share in each market was obtained using expressions (4.1) and (4.11). The values used for parameters μ and β, taken from BELOBABA et al. (2009), were 1.2 and 0.3, respectively. Given the market share, we assigned each market to one of the three pieces of the piecewise linear function we have drawn to represent the relationship between flight frequency and market share (the *R*-square for points of frequency spaced 0.01 in the S-curve and in the piecewise linear function is, for the three pieces, 0.99, 0.98, and 0.95). The recapture rate between demand periods was calculated using expression (4.2), though without considering market share variations throughout the day (because of lack of data for competitors). Examples of market shares and recapture rates are provided in Tables 4.4 and 4.5.

Although the values of recapture rates were considered plausible by TAP officials and are, for most of the markets, in line with the values obtained by JA et al. (2001) – recapture rates between 15% and 55% – further work is necessary to confirm their validity.

Table 4.4 - TAP market share in O/D markets (sample)

Origin	Market share (%)				
	Destination				
	LIS	OPO	FAO	FNC	PDL
AMS	61	83	23	11	46
BRU	66	72	13	84	31
CGD	43	81	22	100	36
EWR	50	83	35	61	100
FRA	74	41	25	61	40
GRU	82	35	100	100	100
LAD	74	89	50	67	100
LHR	62	45	4	82	44
MAD	22	26	5	92	33
MXP	55	64	64	65	19

Table 4.5 - Recapture rate of TAP for flights departing from Lisbon (sample)

Destination	AMS	BRU	CDG	EWR	FRA	GRU	LAD	LHR	MAD	MXP
Recapture rate (%)	33	33	19	42	41	73	63	29	0	26

The information about arrival delays was obtained from EUROCONTROL (for 2007). With this information we determined the "percentage of flights that arrived delayed more than x minutes" in each hour of operation for each airport, and the corresponding cumulative distribution curves. The curve for Lisbon is shown in Figure 4.3. As can be seen there, the majority of flights arrive within 15 minutes of the expected arrival time. Between 8% and 25% of the flights are delayed by more than 15 minutes. Similar curves were obtained for all airports. In the case study we worked with 15-minute slot time windows, therefore the relevant probability values are the ones for 0, 15, 30, 45, 60, 75, 90, 105, and 120 minutes of delay.

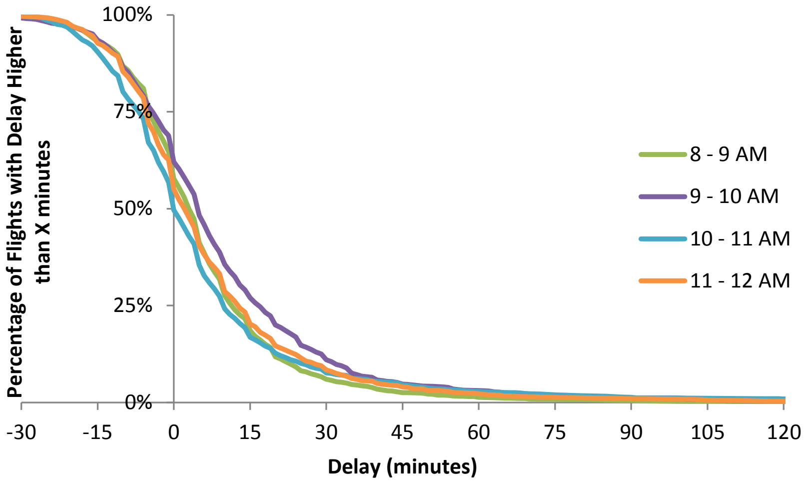

Figure 4.3 - Cumulative arrival delays distribution for Lisbon airport in 2007

The demand for each market considered in the application was supplied by TAP. For markets where TAP offers a non-stop flight, the demand was divided into non-stop and connecting according to the passengers transported by TAP in previous seasons (Table 4.6). In the other markets, passengers were split between non-stop and connecting in the same way as for TAP flights in similar markets (e.g. long-haul Europe/South America, medium-haul Europe/Europe).

The vehicle and aircraft costs per market and aircraft type and the average revenues per market and type of service were also supplied by TAP. Delay costs were taken from the literature. Two different costs were considered – passenger costs and aircraft costs. As noted earlier, passenger delay costs are the direct costs to the airline of disrupted passengers. Though these costs certainly depend on market characteristics (as stated in the model), the available data refer only to average values. These data are provided in a study of passenger delay costs in the US made by BRATU and BARNHART (2006) and in a comprehensive study of passenger and aircraft delay costs in Europe commissioned by the Performance Review Commission of EUROCONTROL to COOK et al. (2004). Both studies report an average minute cost of 0.40 USD per disrupted passenger – which we adopted for all TAP markets. For the aircraft delay costs we used the values in Table 4.7, calculated from the ones presented in the COOK et al. study for short delays (15 minutes) and long delays (65 minutes).

4.5.2 Model Solving

The optimization model was solved on a Quad Core processor with 4GB of RAM using the commercial software Xpress with the optimizer version 20.00.11 (FICO 2009). The model involved over 550,000 integer variables before a set of preprocessing methods were applied to reduce that number to around 50,000. As expected, the computation time varied considerably depending on whether slots were fixed or variable (within one hour). In the first case, the time needed to solve the model was 35.0 seconds when the market share was fixed and 63.5 seconds when the market share was variable. In the second case, the equivalent figures were 342.3 and 642.0 seconds, respectively. This suggests that, when slots are fixed, the model runs fast enough to allow its real-time utilization by a mid-size airline in IATA scheduling conferences. Indeed, the implications of using new slots or changing slots can be estimated in only about one minute, even if market share effects are taken into account. Also, the model can be used

Table 4.6 - Percentage of non-stop and connecting passengers departing from Lisbon (sample)

Passengers departing from Lisbon (%)		
Destination	Non-stop	Connecting
AMS	58	42
BRU	74	26
CDG/ORY	83	17
EWR	52	48
FAO	100	0
FNC	76	24
FRA	73	27
GRU	69	31
LAD	88	12
LHR/LGW	78	22
MAD	89	11
MXP	71	29
OPO	100	0
PDL	83	17

Table 4.7 - Delay costs per aircraft type (USD)

Aircraft type	Delay cost (USD)						
	Minutes of delay						
	15	30	60	90	120	150	180
ER4	5	54	154	254	354	454	554
F 100	18	116	312	507	703	898	1094
A – 319	28	157	416	674	933	1192	1450
A – 320	34	185	488	791	1093	1396	1699
A – 321	38	204	535	867	1198	1529	1861
WIDE	63	315	819	1322	1826	2329	2832

for identifying the best possible slots within one hour of existing (or pre-defined) slots, but in this case real-time utilization is less obvious as results take over ten minutes to obtain.

The main reason for the fast computation times we have observed (as compared with the times reported for other integrated schedule design and fleet assignment models, such as the one presented in LOHATEPANONT and BARNHART, 2004) seems to be because we are dealing with slot-constrained airports to/from which airlines can only fly if they have a slot assigned. Indeed, when slots are allowed to vary within one hour (4 time periods), the time to solve the model increases around 10 times with respect to when slots are fixed. We have performed a test for fixed market share allowing slots to change within three hours (12 time periods), and the computation time was 1349.6 seconds, which is almost 40 times more than when slots are fixed and 4 times more than when they can change within one hour. Other reasons that certainly contribute to explain the good performance of the model are the relatively small size of the airline network both in terms of fleet and number of flights, and the fact that the airline has only two hubs, which limits the number of feasible itineraries.

4.5.3 Main Results

The main results of the application of the optimization model – airline profits, total number of flights, delay costs, average passenger connecting time, and average number of feasible connections per flight – are summarized in Table 4.8. The results shown in this table for the "current schedule with variable market share" situation were obtained fixing the flight schedule but allowing changes in fleet assignment.

Airline profits increase from 23,845 USD/week in the current schedule to 25,092 (+5.2 percent) in the optimum schedule when market shares are variable with flight frequencies and slots are fixed, and to 32,055 (+34.4 percent) when slots are variable (within one hour of the existing slots). If market share effects were ignored, airline profits would also increase, but the magnitude of the increase would be much smaller (from 15,435 to 15,810 or 17,628 USD/week, depending on whether slots are fixed or variable). This underlines the importance of considering market share effects in the flight scheduling (and fleet assignment) process. It is worth noting here that, if delay costs were not taken into account in the optimization model, airline profits would almost vanish (3,241 USD/week instead of 25,092 USD/week if slots were fixed, and 3,721 USD/week instead of 32,055 USD/week if slots were variable) due to a major increase in passenger delay costs. This clearly suggests that neglecting these costs leads to decisions that might seriously endanger the viability of an airline.

The total number of flights, which is 1,618 per week for the current schedule, diminishes to 1,583 (-2.2 percent) in the optimum schedule when market share effects are taken into account if slots are fixed and to 1,592 (-1.6 percent) if slots are variable. The reduction in the number of flights would be much stronger if these effects were ignored (those percentages would be -14.2 and -11.9, respectively). This is consistent with the widespread idea that airline competition is responsible for a considerable increase in flight frequencies.

The total delay costs depend on the number of flights. Hence we compare the percentage of delay costs relative to total costs rather than their absolute values. For the current schedule that percentage is 9.8 for variable market shares and 9.7 for fixed market shares. In the optimum schedule, the first figure shrinks to 8.4 (-14.3 percent) if slots are fixed and to 7.4 percent (-24.5 percent) if slots are variable. The reduction in delay costs would be even greater if market share effects were not considered (-24.5 percent and -26.5 percent). As can be seen in Table 4.8, the reduction of these costs is essentially due to a major decrease in passenger delay costs.

Passenger delay costs are inversely related with the average passenger connecting time, therefore connecting time increases when the schedule is optimized. For the current schedule, the average passenger connecting time is 86.3 minutes when market share effects are considered and 83.5 minutes when these effects are ignored. In the optimum schedule, if slots are fixed, the equivalent figures are 93.2 minutes (+8.0 percent) and 96.1 minutes (+15.1 percent), and, if slots are variable, they are 108.5 minutes (+25.7 percent) and 112.6 (+34.9 percent). Although these connecting time changes are noticeable, their contribution to total travel time is rather small. Indeed, for the intercontinental markets, the average travel time increases 1.3 or 0.9 percent when slots are fixed depending on whether the market share is fixed or variable, and 3.5 or 3.0 percent when slots are variable. Since time costs are only a fraction of total travel costs, the implications for demand should be minor (as it was assumed they would be). For the European markets, the equivalent percentages are 3.8 and 2.7 percent when slots are fixed, and 10.1 and 8.5 percent when they are variable, meaning that, at least in the latter case, demand effects might deserve further consideration. Finally, the average number of feasible connections, which is 5.98 in the current situation, increases between 4.3 percent and 9.2 percent (the maximum increase occurs when the slots are fixed and the market share is variable). The flights with more feasible connections are the ones from/to Brazil (with more than 20 feasible connections), because the maximum connecting time is high (as the flight time is large), and those to the Azores.

In Table 4.9 are presented the results obtained for Friday, the busiest day of the week, considering that slots are fixed and that market shares are fixed or variable.

Table 4.8 - Summary of results for a week of operations

Model features				Indicators						
Schedule	Slots	Market share	Fleet Assignment	Airline profits	Total flights	Delay cost			Waiting time (avg.)	Average feasible connections
						Aircraft	Pax	Total		
				USD		% of total costs			Minutes	
Current	Fixed	Fixed	Fixed	15435	1618	4.9	4.9	9.7	83.5	5.98
	Fixed	Variable	Variable	23845	1618	5.5	4.2	9.8	86.3	5.98
Optimal	Fixed	Fixed	Variable	15810	1388	5.3	2.1	7.4	96.1	6.27
	Fixed	Variable	Variable	25092	1583	5.3	3.1	8.4	93.2	6.53
	Variable	Fixed	Variable	17628	1425	5.3	19	7.2	112.6	6.36
	Variable	Variable	Variable	32055	1592	5.2	2.2	7.4	108.5	6.24

Table 4.9 - Summary of results for Friday (busiest day of the week)

Model features				Indicators						
Schedule	Slots	Market share	Fleet Assignment	Airline profits	Total flights	Delay cost			Waiting time (avg.)	Average feasible connections
						Aircraft	Pax	Total		
				USD		% of total costs			Minutes	
Current	Fixed	Fixed	Fixed	4376	240	5.2	4.8	10.1	87.6	6.18
	Fixed	Variable	Variable	4376	240	5.2	4.8	10.1	87.6	6.18
Optimal	Fixed	Fixed	Variable	5787	212	5.6	2.5	8.1	90.7	6.48
	Fixed	Variable	Variable	6481	234	5.2	2.7	7.9	94.4	6.53

When the market share is fixed, airline profits for the optimum schedule increase 31.9 percent (from 4,376 to 5,787 USD/day) in relation to the current situation. The number of flights is reduced from 240 to 212 (-11.7 percent). The connections where reductions occur correspond to medium-haul markets where TAP faces strong competition (Figure 4.4). The only connection where a new flight is added is LIS-OPO (where TAP has no competitors). The weight of delay costs decreases 19.5 percent (to 8.1 percent), the average connecting time increases 5.5 percent (to 90.7 minutes), and the average number of feasible connections per flight increases 4.9 percent (to 6.48). The decrease in delay costs is only due to the reduction of the weight of passenger delay costs (-48.0 percent), because the weight of aircraft delay costs increases (+5.5 percent).

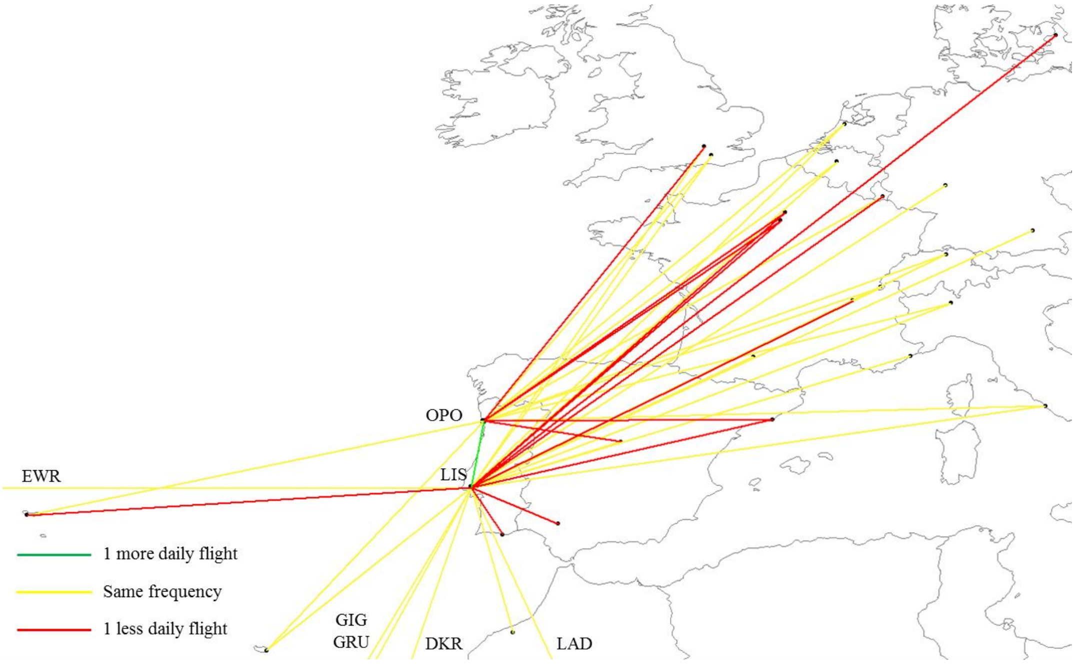

Figure 4.4 - Changes in daily flight frequencies with fixed market shares – Fridays

When the market share is variable, airline profits increase 19.2 percent (from 5,438 to 6,481 USD/day) in relation to the current schedule, though not as much as when market share is fixed. The number of flights decreases, but only to 234 (-2.5 percent). In total, Lisbon loses 2 flights and Oporto loses 4 flights (Figure 4.5). There is a transfer of flights from OPO to LIS in the connections with MAD, LHR and ORY. These changes reflect the higher competition among legacy carriers that exists in the Lisbon airport. The weight of delay costs decreases 24.3 percent (to 7.9 percent), the average connecting time increases 7.8 percent (to 94.4 minutes), and the average number of feasible connections per flight increases 5.7 percent (to 6.53).

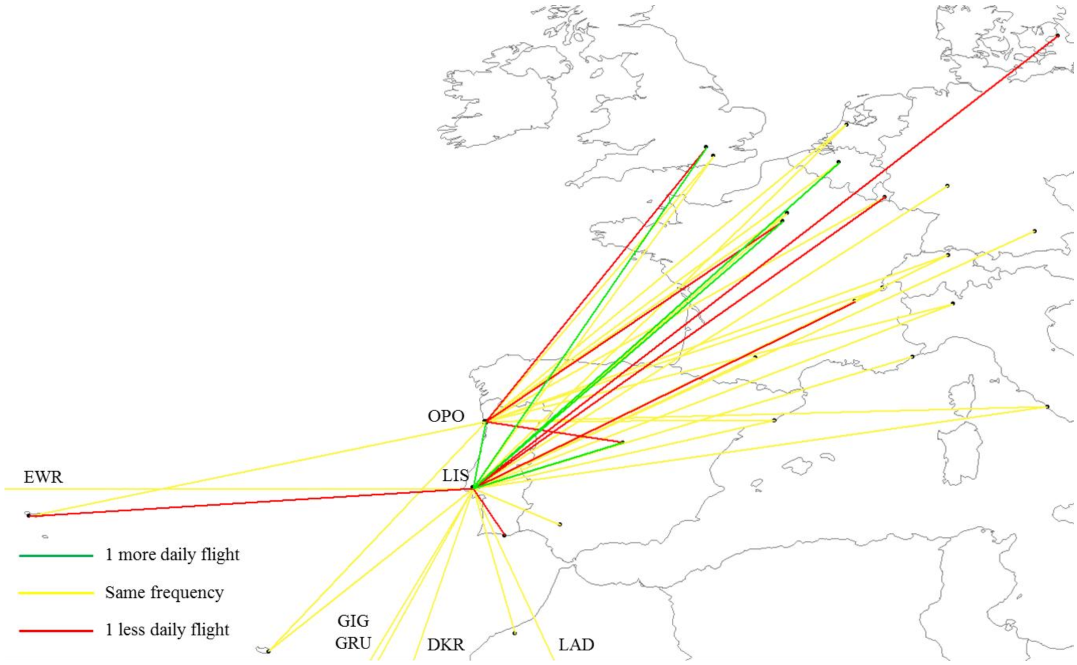

Figure 4.5 - Changes in daily flight frequencies with variable market shares – Fridays

4.5.4 Sensitivity Analysis

In order to assess the implications of the assumptions upon which the case study and underlying model are based, a sensitivity analysis was performed with respect to five model parameters – average revenues per market, vehicle costs, aircraft delay costs, passenger delay costs, and recapture rate per market. For each parameter four values were tested: -20, -10, +10, and +20 percent in relation to the base values (i.e. the values considered in the previous subsection). The results were calculated for Friday considering fixed slots and variable market shares, and were compared with respect to airline profits, number of flights, and average passenger connecting time (Table 4.10).

Changes in average revenues per market (r) have a major influence on airline profits – when Δr=-20% profit decreases to 5,295 USD/day (-18.3%), and when Δr =+20% profit increases to 7,615 USD/day (+17.5%). Comparatively, the number of flights changes slightly, going down from 234 to 230 (Δr=-20%) or up to 238 (Δr =+20%). The average passenger connecting time varies between 91.0 minutes (Δr=-10%) and 95.2 minutes (Δr =+20%), which is a –3.1% and +0.8% variation from the base value (94.4 minutes). The variation of vehicle costs (c_V) also has a significant impact on airline profits, but clearly smaller than the variation of average revenues per market – they rise from 5,821 USD/day (-10.2%) when Δc_V =+20% to 7,229 USD/day (+11.5%) when Δc_V =-20%. In contrast, the changes in number of flights are much larger, being as few as 215 (-8.1%) when Δc_V =+20% and as much as 240 when Δc_V =-20%. The average passenger connecting time also varies considerably, ranging between 83.5 minutes (-11.5%) when Δc_V =-20% and 106.5 minutes (+12.8%) when Δc_V =+20%.

Changes in aircraft delay costs (c_D) lead to variations in airline profit that oscillate between -2.8 percent (Δc_D =+20%) and +3.6 percent (Δc_D =-20%). However, they have almost the same impact on the number of flights as the average revenues per flight – for Δc_D=+20% the number of flights is 231, and for Δc_D=-20% is 236. The average passenger connecting time varies from 89.6 minutes (-5.1%) to 98.1 minutes (+3.9%) when Δc_D =-20% and Δc_D =+20%, respectively.

Table 4.10 - Summary of sensitivity analysis results

Parameter	Variation (%)	Indicators					
		Airline profits		Total flights		Waiting time (avg.)	
		USD	Variation (%)	Total	Variation (%)	Minutes	Variation (%)
Average revenues per market	-20	5295	-18.3	230	-1.7	91.5	-3.1
	-10	5885	-9.2	233	-0.4	91	-3.6
	10	7142	10.2	235	0.4	93.4	-1.1
	20	7615	17.5	238	1.7	95.2	0.8
Vehicle costs	-20	7229	11.5	240	2.6	83.5	-11.5
	-10	6769	4.4	238	1.7	89.3	-5.4
	10	6093	-6	225	-3.8	98.7	4.6
	20	5821	-10.2	215	-8.1	106.5	12.8
Aircraft delay costs	-20	6714	3.6	236	0.9	89.6	-5.1
	-10	6575	1.5	234	0	93.6	-0.9
	10	6427	-0.8	232	-0.9	96.1	1.8
	20	6300	-2.8	231	-1.3	98.1	3.9
Passenger delay costs	-20	6598	1.8	235	0.4	87.6	-7.2
	-10	6500	0.3	234	0	92.6	-1.9
	10	6455	-0.4	234	0	96.6	2.3
	20	6390	-1.4	232	-0.9	98.6	4.5
Recapture rate	-20	6183	-4.6	237	1.3	93.6	-0.8
	-10	6381	-1.6	235	0.4	95.8	1.5
	10	6630	2.3	234	0	94.9	0.5
	20	6824	5.3	231	-1.3	91.4	-3.2

The variation in passenger delay costs (c_P) influences airline profits less than aircraft delay costs, since changes range from -1.4% (Δc_P =+20%) and +1.8% (Δc_P =-20%). The same occurs with the number of flights, which go down to 232 (Δc_P =+20%) or up to 235 (Δc_P =-20%). But, with respect to the average passenger connecting time, the opposite happens – when Δc_P =-20% this time decreases to 87.6 minutes (-7.2%), and when Δc_P =+20% it increases to 98.6 minutes (+4.5%).

Changes in recapture rates (α) the airline profits vary from 6,183 USD/day (-4.6%) when $\Delta\alpha$=-20% to 6,824 USD/day (+5.3%) when $\Delta\alpha$=+20%, that is, their effect on profit is stronger than the effects of changes in delay costs. The number of flights diminishes from 234 to 231 ($\Delta\alpha$=+20%) or augments to 237 ($\Delta\alpha$=-20%), approximately the same changes as when delay costs change. The implications upon the average passenger connecting time are rather small (and irregular), ranging between 95.8 minutes (+1.5%) when $\Delta\alpha$=-10% and 91.4 minutes (+3.2%) for $\Delta\alpha$=+20%.

Overall, it can be said that variations in average revenues per market, vehicle costs, and recapture rates have a stronger impact on airline profits than aircraft and passenger delay costs. This seems to happen in part because the number of flights and average passenger connecting times change with delay costs approximately as much as they change in response to the variation of average revenues per market. Thus, it looks like that the consideration of delay costs in the optimization model leads to flight schedules (and fleet assignments) that contribute in a significant manner to the stabilization of airline profits. This is, we believe, an important point favoring the utilization of the model in practice.

4.6 Conclusions

The model presented in this chapter addresses integrated flight scheduling and fleet assignment problems from a robust scheduling perspective. Its main contribution lies in the fact that the aircraft and passenger delay costs involved in these problems are explicitly taken into account. Other contributions include the consideration of slot-constrained airports, O/D-based travel demand, airline competition and airline cooperation. Taken together, these contributions give answer to some of the main features of the problems dealt with in this chapter.

The practical usefulness of the model was tested on a case study involving the main network of TAP Portugal. Even though the results we have obtained rely on some simplifications, they provide useful insights into how the Portuguese legacy carrier might improve their flight schedule and fleet assignment. The improvement could lead to an increase in TAP's expected profits, while diminishing the total number of flights and increasing slightly the average passenger connecting time. The increase is estimated at about 5 percent even if the slots operated by TAP in all airports of their main network do not change. But, if the slots could change freely within one hour of the current slots, the increase could be substantially higher. The fact that the model has run in only about one minute when slots were fixed is extremely important, because this allows the real-time utilization of the model in scheduling conferences. These findings clearly indicate that the model is a valuable addition to the airline planning toolbox.

Despite the strengths of the model, we recognize that it has two main limitations. First, the demand captured by airlines is taken as given, instead of depending on fares and other passenger costs (including time costs); second, the reaction of rival airlines is assumed to be known. The former limitation seems relatively easy to cope with, but the latter could only be overcome through a much more complex model – so more complex that we doubt it could be of practical interest. Moreover, in slot-constrained airport networks (as the ones outside the US) the changes in airline slots in consecutive seasons are typically small.

In the future, part of our activity in this area of research will be devoted to improving the model with respect to the first limitation identified above. The other part will be dedicated to testing the applicability of the model to networks of larger airlines. It may well be that, for such airlines, the model becomes impossible to solve within acceptable computation effort when commercial software is used. If this is the case, efficient specialized methods, exact or heuristic, would then have to be developed.

Chapter 5

Setting Public Service Obligations in Low-Demand Air Transportation Networks: Application to the Azores

5.1 Introduction

In response to deregulation of air transportation, commercial airlines were expected to concentrate their networks on profitable routes and to reduce services and/or increase fares in thinner markets. Also, they were expected to change the configuration of their networks to adopt a hub-and-spoke structure, thus decreasing both demand variability per leg and fares (in thicker markets) but increasing travel times (REYNOLDS-FEIGHAN, 1995a). Both types of reaction go against the interests of regions without sufficient passenger demand to have profitable legs – regions where air transportation often plays a crucial role with respect to the mobility of people and goods, as well as to the development of tourism. Because of this, governments have decided to accompany the air transportation deregulation process with the adoption of subsidy schemes aimed at mitigating the consequences that could be anticipated with respect to low-demand regions (SANTANA, 2009). Currently, there are two major subsidy schemes: the Essential Air Services (EAS) program, launched in the USA in 1978; and the Public Service Obligation (PSO) system, launched in Europe in 1992. Detailed information about both schemes and their differences can be found in REYNOLDS-FEIGHAN (1995b) and BRAATHEN (2011).

The PSO system was put forward as a core part of the legislation pertaining to the deregulation of air transportation in Europe (CEC, 1992a; CEC, 1992b; CEC, 1992c; CEC, 2008). The system can be briefly described as follows (Figure 5.1): (1) A government (aviation authority) feels the need to open new PSO routes, domestic or international, to/from low-demand regions. (2) The government defines the level of service for those routes and opens a call for bidders – all airlines with a permit to operate in Europe can bid. (3) Airlines bid for the routes without subsidies, and the government assigns the routes to the best proposal; otherwise, if no airlines are willing to operate those routes, the government launches a new bidding process in which subsidies are granted to the airlines. (4) Airlines bid again for the routes, this time knowing the subsidies. (5) The government decides which airline will have the right to fly each route. (6) The process is repeated every three years. For more information about the PSO system, readers are referred to WILLIAMS (2005).

The items included in the PSO requirements vary significantly from country to country. The minimum flight frequency between airports and the minimum number of seats available per flight leg are among the most frequent items imposed by governments. With respect to flight schedules, earliest departure times and latest arrival times are sometimes included in the PSO requirements to guarantee daily round trips. In order to ensure good connectivity, governments can set the maximum number of stops between airports or the maximum waiting time between flights. Governments can also specify aircraft features such as the minimum number of seats or even the aircraft type (jets vs. turbo-props). Finally, discounts for students, residents, and/or retired people can be explicitly contained in the PSO requirements.

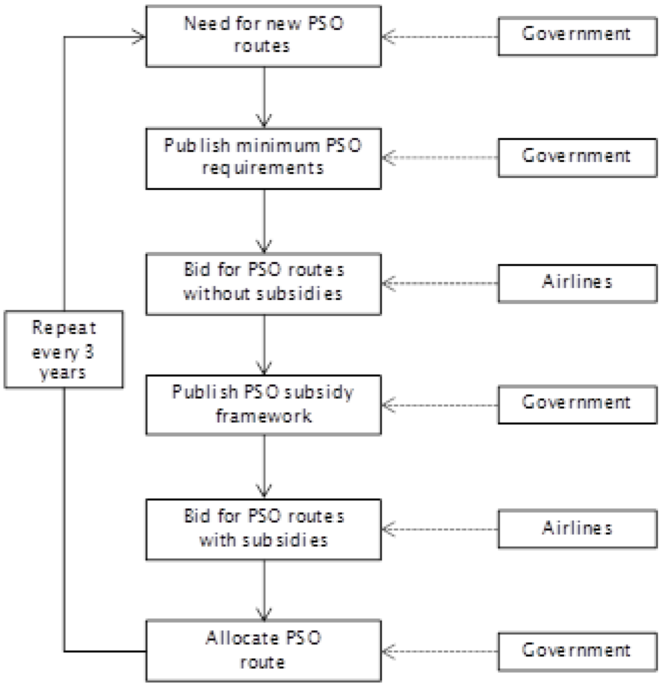

Figure 5.1 - Scheme of the PSO system

The number of routes operated in Europe – within a country or between European countries – under PSO contracts has been growing consistently throughout time: they were 67 in 1997, 168 in 2001, 230 in 2003 (MINSHALL, 2004), and, according to CEC (2010), at least 260 routes in 2010 (the expression “at least” is used because the number of routes changes during the year). Currently, eight EU countries plus Norway and Iceland offer PSO services, awarding financial compensation to airlines operating regular services to/from low-demand regions. Norway and France are the countries with the most PSO routes – respectively, 61 and 41 routes in 2010 (CEC, 2010). The country where the domestic network is most dependent on this kind of subsidies is Portugal – in 2001, 40 percent of the domestic passengers in Portugal traveled on PSO routes compared to around 10 percent in France, Norway, and Scotland (WILLIAMS and PAGLIARI, 2004). The level of subsidies varies widely across countries, being around 120 EUR per passenger in Germany and only slightly above 20 EUR per passenger in France and Portugal (BRAATHEN, 2011).

In this chapter, is proposed a decision approach designed to assist governments (aviation authorities) in the definition of PSO requirements. The approach is based on an integrated flight scheduling and fleet assignment (IFSFA) model to determine the air transportation network that minimizes the total social costs of satisfying a given origin/destination (O/D) demand, as well as the amount of public subsidies necessary to finance it. The IFSFA model differs from traditional models, which are sought for airlines and aim at maximizing profits (LOHATEPANONT and BARNHART, 2004; SHERALI et al., 2010). To the best of our knowledge, the literature about the subsidization of air transportation has never dealt with these kind of operational issues before, focusing instead on the analysis and comparison of subsidy schemes (REYNOLDS-FEIGHAN, 1995a; GRAHAM, 1998; SANTANA, 2009; METRASS-MENDES and DE NEUFVILLE, 2010; LIAN, 2010; BRAATHEN, 2011).

The remainder of the chapter is organized as follows. Next, in consecutive sections, is described the proposed decision approach and the underlying IFSFA model. The usage of the approach is then illustrated for one of the main networks fully operated according to a PSO system – the network of the Azores (Portugal). In the last section, we assess the main strengths and weaknesses of the decision approach and indicate some guidelines for future research.

5.2 Decision Approach

The problem faced by a government when setting PSO requirements for the air transportation network of a low-demand region is quite complex. The decision approach proposed below is designed to cope with this complexity. The objective of the government is assumed to be the minimization of the total social costs of the network. This objective has to be pursued while balancing the demand to satisfy and the level of service to offer with the amount of public subsidies the government can afford to pay to the airlines that operate the network. The demand depends on the costs incurred by passengers, which consist of airfares and time costs, and particularly of the costs corresponding to the waiting time of connecting passengers, which in turn depend on the flight schedules, thus on the level of service offered to passengers.

The proposed decision approach comprises five stages (Stages 1 to 5), to be repeated sequentially until the amount of public subsidies the government needs to pay complies with the budget available to finance the network (Figure 5.2).

In Stage 1, the government sets, for all markets m (O/D pairs between airports j and k), the target number of passengers (or demand targets) q_m to be transported by the air transportation network, taking into account historical information and socioeconomic objectives related, for example, with access to public facilities such as secondary and higher education schools, hospitals, or tribunals. These targets are expected to reflect the views of the government on the mobility needs of the region under consideration. The public subsidies involved in the air transportation network will naturally depend on the demand targets adopted, and may be excessive in the face of budgetary constraints. If this is the case, these targets will have to be revised in a later stage of the approach.

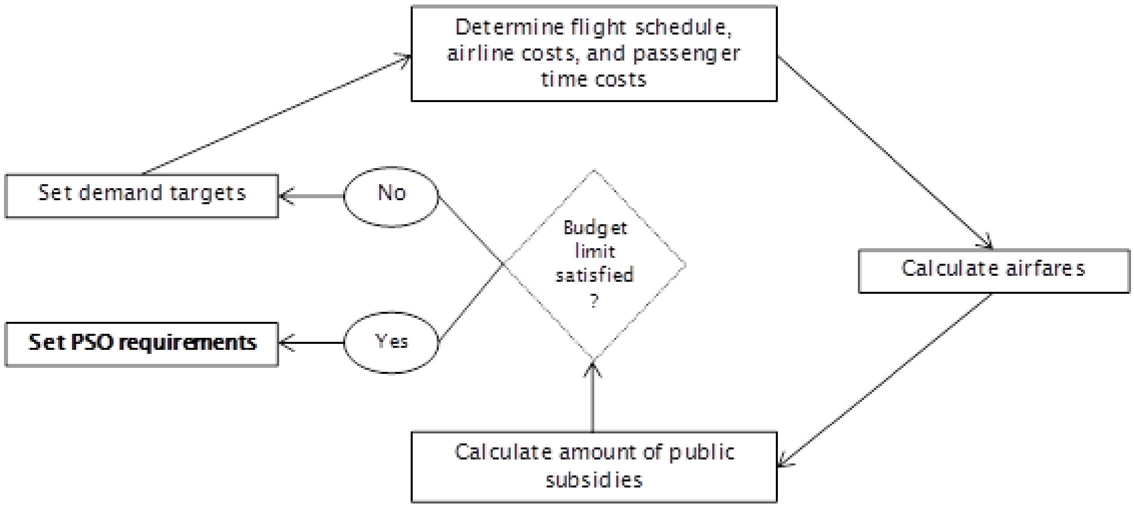

Figure 5.2 - Scheme of the decision approach

In Stage 2, the flight schedule (and fleet assignment) that minimizes the total social costs incurred to satisfy the demand targets defined in Stage 1 is determined using the IFSFA model described in the next section. The total social costs consist of airline costs (c^A) and passenger time costs (c^P). Airline costs consist of ground and system operating costs and direct operating costs (BELOBABA et al., 2009, Chapter 5). Passenger time costs consist of on-board time costs (c^B) and waiting time costs (c^W). The IFSFA model can reflect typical PSO requirements such as the minimum flight frequency between airports and the minimum number of seats available per flight.

In Stage 3, airfares for all markets, p_m, are calculated using a demand function relating the number of passengers with: (1) passenger costs (airfares plus the time costs determined in Stage 2); (2) socioeconomic variables reflecting the size of the markets (e.g., population and income); and (3) service variables reflecting, for example, intermodal competition. That is, airfares are obtained through the following expression:

$$q_m = f\left(p_m, c^B_m + c^W_m, \bar{v}_m\right), \forall m \in \boldsymbol{M} \tag{5.1}$$

where $\boldsymbol{M}$ is the set of markets and $\bar{v}_m$ is the vector of socioeconomic and service variables for market *m*.

In Stage 4, the amount of public subsidies, *g*, is calculated as the difference between the airline costs determined in Stage 2 and the revenues made by the airline from the airfares determined in Stage 3. That is:

$$g = c_A - \sum_{m \in \boldsymbol{M}} p_m \, q_m \tag{5.2}$$

Finally, in Stage 5, the amount of public subsidies is compared with the budget available to finance the air transportation network of the region. If the budget is exceeded (or cannot be increased), the demand targets should be updated and the process needs to be repeated starting from Stage 1. Otherwise, if the budget is satisfied, the government can set the PSO requirements according to the results of the approach.

To conclude this section it is worth noting that the decision approach described above is general and may need adaptions to specific situations. This is, for instance, the case when discounts for students, residents, and/or retired people are to be applied, would require the segmentation of demand targets and consideration of different airfares for the same market.

5.3 Optimization Model

The integrated flight scheduling and fleet assignment model underlying the decision approach described in the previous section is designed for application to a given planning period (e.g., one week or one day) divided in small time windows (e.g. 10, 15, or 30 minutes). The objective of the model is minimization of the total social costs of the air transportation network. This is a different objective from typical IFSFA models, that reflect the focus of airlines on maximization of profit.

Due to the importance to airlines, extensive literature is available about flight scheduling – e.g., BERGE and HOPPERSTAD (1993), ERDMANN et al. (2001), and BARNHART and KIM (2005) – and fleet assignment problems – e.g., ABARA (1989), HANE et al. (1995), BARNHART et al. (2002), and DUMAS et al. (2009). More recently, these problems are being addressed in an integrated way (see, e.g., LOHATEPANONT and BARNHART, 2004, and SHERALI et al., 2010). However, as far as we know, there are no IFSFA models available for air transportation networks operated under PSO requirements.

For formulating the model, consider the following notation:

<u>Sets:</u>

A - set of airports indexed by *j* or *k*; ***R*** - set of aircraft types indexed by *r*; ***M*** - set of markets indexed by *m*; ***N*** - set of nodes indexed by *n* (a node consists of an airport and a time window, see Figure 5.3); ***I*** - set of itineraries indexed by *i* (an itinerary consists of a departure node, an arrival node, and possible connecting nodes); ***G*** - set of ground arcs indexed by *g* (ground arcs represent consecutive time windows for the same airport);

$\boldsymbol{G^O_n}$ - set of outbound ground arcs from node n (that is, ground arcs that start at node n); $\boldsymbol{G^I_n}$ - set of inbound ground arcs to node n (that is, ground arcs that end at node n); $\boldsymbol{G^C}$ - set of ground arcs that pass the count time; $\boldsymbol{F}$ - set of flight arcs indexed by f (a flight arc consists of a departure node and an arrival node); $\boldsymbol{F^O_n}$ - set of outbound flight arcs from node n; $\boldsymbol{F^I_n}$ - set of inbound flight arcs to node n; $\boldsymbol{F^C}$ - set of flight arcs that pass the count time; $\boldsymbol{F_{jk}}$ - set of flight arcs for leg jk (departing from airport j and arriving at airport k).

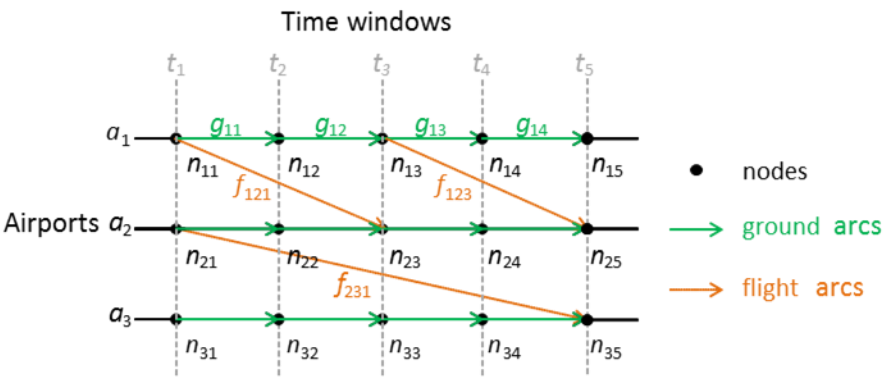

Figure 5.3 - Representation of nodes, flight arcs, and ground arcs

<u>Parameters</u>: d_m - number of passengers for market m; c^F_{fr} - flight costs for an aircraft of type r to fly arc f (EUR per flight); c^S_{gr} - stoppage costs of having an aircraft of type r on ground arc g (EUR per aircraft); c^B_i - on-board time cost for a passenger on itinerary i (EUR per passenger); c^W_i - waiting time cost for a passenger on itinerary i (EUR per passenger); s_r - capacity of an aircraft of type r; l_f - maximum load factor for flight arc f; δ^f_i - parameter equal to 1 if flight arc f belongs to itinerary i, and 0 otherwise; δ^m_i - parameter equal to 1 if itinerary i serves market m, and 0 otherwise; $x_{min_{jk}}$ - minimum number of flights to be offered on leg jk; $s_{min_{jk}}$ - minimum number of seats to be offered on leg jk.

Decision Variables: u_i - number of passengers assigned to itinerary i; x_{fr} - number of flights by aircraft type r on arc f; y_{gr} - number of aircraft of type r on ground arc g; z_r - number of aircraft of type r.

Using this notation, the objective function of the optimization model can be formulated as follows:

$$\min C = \sum_{f \in \boldsymbol{F}} \sum_{r \in \boldsymbol{R}} c_{fr}^F x_{fr} + \sum_{g \in \boldsymbol{G}} \sum_{r \in \boldsymbol{R}} c_{gr}^S y_{gr} + \sum_{i \in \boldsymbol{I}} c_i^B u_i + \sum_{i \in \boldsymbol{I}} c_i^W u_i \quad (5.3)$$

The objective function (5.3) represents the minimization of the total social costs of the air transportation network (except for airline ground and system operating costs, which are taken as fixed). The costs considered encompass airline operating costs and passenger time costs. The airline operating costs are divided in two components: the costs of flying the arcs (flight costs), which consist of vehicle, fuel, and crew costs; and the costs of having aircraft stopped at an airport (these costs will normally be larger when aircraft are outside airlines' bases). The passenger time costs are divided in on-board time costs and waiting time costs.

The model includes the following sets of constraints:

$$\sum_{g \in \boldsymbol{G}^C} y_{gr} + \sum_{f \in \boldsymbol{F}^C} x_{fr} \le z_r, \ \forall r \in \boldsymbol{R} \quad (5.4)$$

Constraints (5.4) limit the use of aircraft to the available fleet. For each aircraft type r the number of aircraft on the ground plus the number of aircraft in the air equal the total number of aircraft available.

$$\sum_{f \in \boldsymbol{F}_n^I} x_{fr} + \sum_{g \in \boldsymbol{G}_n^I} y_{gr} = \sum_{f \in \boldsymbol{F}_n^O} x_{fr} + \sum_{g \in \boldsymbol{G}_n^O} y_{gr}, \ \forall n \in \boldsymbol{N}, r \in \boldsymbol{R} \quad (5.5)$$

Constraints (5.5) guarantee aircraft continuity per node and aircraft type. For each aircraft type *r* at each node *n*, the sum of inbound flight and ground arcs equals the sum of outbound flight and ground arcs (that is, the number of aircraft that arrive or were parked on a given airport in a given time window is equal to the number of aircraft that take-off or stay parked).

$$\sum_{r \in \boldsymbol{R}} l_f s_r x_{fr} \geq \sum_{i \in \boldsymbol{I}} \delta_i^f u_i, \ \forall f \in \boldsymbol{F} \tag{5.6}$$

Constraints (5.6) limit the number of passengers assigned to each flight to the number of available seats. This number is equal to the number of seats of aircraft type *r* flying arc *f* multiplied by the maximum allowed load factor per arc. Passengers on itineraries *i* can be assigned to flight arc *f* if that flight arc belongs to these itineraries (in this case, δ_i^f is equal to 1). To account for demand uncertainty, the load factor can have an upper limit below one, which is especially important in low-demand markets where demand uncertainty tends to be high (SWAN, 2002).

$$q_m = \sum_{i \in \boldsymbol{I}} \delta_i^m u_i, \forall m \in \boldsymbol{M} \tag{5.7}$$

Constraints (5.7) guarantee that the demand per market is satisfied, that is, all passengers in market *m* are assigned to an itinerary *i* serving market *m*.

$$\sum_{f \in \boldsymbol{F_{jk}}} \sum_{r \in \boldsymbol{R}} x_{fr} \geq x_{\min_{jk}}, \ \forall j,k \in \boldsymbol{A} \tag{5.8}$$

$$\sum_{f \in \boldsymbol{F_{jk}}} \sum_{r \in \boldsymbol{R}} s_r x_{fr} \geq s_{\min_{jk}}, \ \forall j,k \in \boldsymbol{A} \tag{5.9}$$

Constraints (5.8) and (5.9) exemplify typical PSO requirements. They set a lower bound for the number of flights and the number of seats per leg during the planning period.

Expressions (5.10) and (5.11) specify the type and domain of the decision variables, and complete the formulation of the model.

$$x_{fr}, y_{gr} \text{ non-negative integers}, \forall f \in \boldsymbol{F}, r \in \boldsymbol{R}, g \in \boldsymbol{G} \tag{5.10}$$

$$u_i \geq 0, \forall i \in \boldsymbol{I} \tag{5.11}$$

5.4 Case study

The decision approach (and underlying optimization model) proposed before was applied to a case study involving the air transportation network of the Azores (Portugal). The archipelago of the Azores comprises nine islands located in the Atlantic Ocean about 1,500 km west of Lisbon with a total population of around 245,000. The domestic air transportation network is subsidized by the Azorean government, and permission to operate the network has been granted to SATA for three years. The network comprises nine airports, one in each island (Figure 5.4). The main airport is located in Ponta Delgada, the capital city of Azores. SATA has two operation bases, established at the airports of Ponta Delgada (PDL) and Terceira (TER). The connections of the archipelago with mainland Portugal, Europe, and North America are made essentially through these two airports. The fleet used by SATA to run the network consists of six Bombardier Dash 8 aircraft – two DHC-8-200 (DH2) with 37 seats and four DHC-8-400 (DH4) with 80 seats. The PSO requirements set by the government cover, among others, the following items: minimum number of weekly flights and seats per leg; days of operation for the non-daily flights; and airfares for residents and students. The minimum number of weekly flights per leg for the various months of the year is shown in Table 5.1.

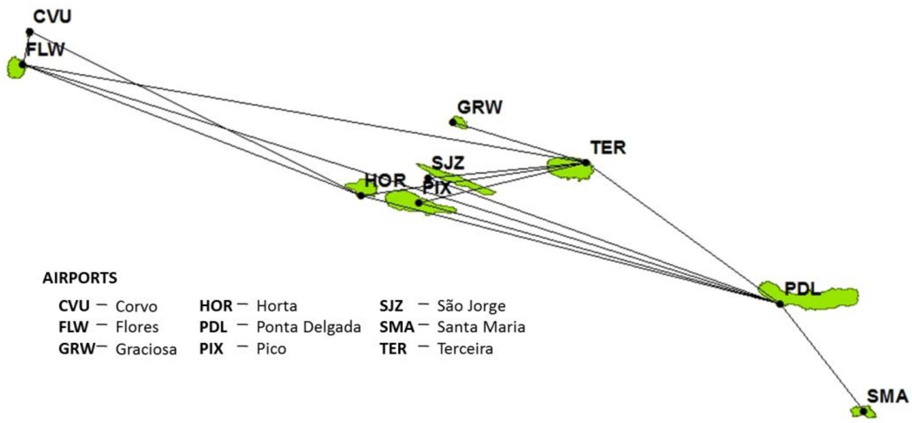

Figure 5.4 - Current air transportation network of the Azores

Table 5.1 - Minimum number of weekly flights under PSO requirements

Flight leg	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
PDL - TER	22	22	22	22	22	22	26	26	22	22	22	22
PDL - HOR	6	6	6	11	11	11	17	17	11	11	6	6
PDL - SMA	9	9	9	10	10	10	14	14	10	10	9	9
PDL - SJZ	3	3	3	3	3	3	6	6	3	3	3	3
PDL - PIX	2	2	2	7	7	7	9	9	7	7	2	2
PDL - FLW	2	2	2	2	2	2	4	4	2	2	2	2
TER - HOR	11	11	11	11	11	11	14	14	11	11	11	11
TER - SJZ	8	8	8	8	8	8	9	9	8	8	8	8
TER - PIX	7	7	7	7	7	7	8	8	7	7	7	7
TER - FLW	2	2	2	2	2	2	4	4	2	2	2	2
TER - GRW	7	7	7	7	7	7	8	8	7	7	7	7
TER - CVU							3	3				
HOR - FLW	4	4	4	4	4	5	5	5	5	4	4	4
HOR - CVU	3	3	3	3	3	3	3	3	3	3	3	3
FLW - CVU	2	2	2	2	2	2	2	2	2	2	2	2

The case study compares the current air transportation network of the Azores (corresponding to the current PSO requirements) with the optimum networks obtained through the decision approach proposed in Section 5.2. The comparison was initially made at the network level, and then for the different airports/islands of the archipelago. The optimum networks were established for a maximum load factor per leg of 90 percent, considering both no limit on the maximum waiting timing faced by connecting passengers and a limit of 3 hours (for each stop). The variability of results with changes in some important parameters was assessed through a sensitivity analysis.

The results obtained for the case study indicate that, for the current number of passengers per market, the air transportation network of the Azores could be clearly better for all parties involved – the passengers who use it (including those who use it in connecting itineraries), the airline who operates it, and the government who subsidizes it. Indeed, the total social costs of the network could decrease by 7.1 percent, as a result of reductions of 14.9 and 1.3 percent airline operating costs and passenger time costs, respectively. The amount of public subsidies could drop by 6.7 percent and the airfares could drop by 8.3 percent. The gains would naturally be smaller if more attention were paid to the waiting times of connecting passengers, but would still be noteworthy. It should be noted that, if this decrease in the amount of public subsidies was considered by the government to be unsatisfactory, then, according to the decision approach proposed in Section 5.2, the target number of passengers would have to be lowered.

In the remainder of this section, is provided detailed information on the data used in the case study, on the results obtained at the network level and at the airport/island level, and on the computational effort required to solve the optimization model underlying the decision approach.

5.4.1 Study Data

The following data was used in the case study: demand targets for each market; flight time per leg; flight costs per leg and aircraft type, stoppage costs, and airline ground and system operating costs; value of time; minimum number of weekly flights and seats per leg and maximum airfares per market (both set as PSO requirements), and current number of flights; population and income per island, and availability of boat services between islands. We have used data for a heavy (but not a peak) month, September, for the last year they were available (2009).

The demand target for each market was assumed to be the daily number of passengers in that market in September 2009. In that month, a total of 35,317 passengers traveled by air inside the Azores, distributed per market as described in Table 5.2 (data supplied by SATA). The number of passengers on markets connecting the Azores to external airports were assumed to be independent of the airfares charged in domestic flights.

Table 5.2 - Number of passengers per market (September 2009)

Market	PDL	TER	HOR	SMA	SJZ	PIX	FLW	GRW	CVU
PDL	-	3666	2107	1790	872	1248	870	385	68
TER	3596	-	1268	155	1147	497	390	860	34
HOR	2571	1156	-	65	18	0	517	90	75
SMA	2139	187	63	-	14	46	42	46	4
SJZ	1159	1165	25	33	-	4	7	63	0
PIX	1636	822	3	58	6	-	9	23	0
FLW	1339	361	536	34	19	10	-	30	16
GRW	362	1185	86	37	55	53	9	-	0
CVU	67	44	57	4	0	2	12	0	-

The flight costs per leg and aircraft type were determined by multiplying the aircraft's operating costs per block-hour (BH) with the leg's flight time. The operating costs essentially include fuel, crew, and maintenance, and were calculated through linear regression analysis using the information for aircraft with less than 100 seats available at EUROCONTROL (2009). The values obtained were 1,363 EUR per BH for the DHC-8-200 and 2,156 EUR per BH for the DHC-8-400. The stoppage costs per BH were considered to be nil for SATA base airports (PDL and TER) and to be the same as the crew costs, which were estimated to be 1/3 of the flight costs, for the remaining airports (SWAN and ADLER, 2006). The airline ground and system operating costs were assumed to be equal to the direct operating costs for the current network (BELOBABA et al., 2009, Chapter 5).

The value of time, used to calculate passenger time costs (on-board and waiting), was assumed to be 5 EUR/hour. This small value of time reflects the low average income of the Azorean population.

The maximum airfares per market and the minimum number of weekly flights and seats per leg are shown in Tables 5.3 and 5.4, respectively. Table 5.4 also provides information on the current number of flights, which is 234 per week, 17 percent more than the minimum required (200). The heaviest leg is PDL-TER with 50 flights per week, 6 more than required. The smallest airport is CVU with only 10 flights per week.

The flight time per leg was taken to be the same as the current flight time and is shown in Table 5.4.

The population and income per island were used to estimate the demand function (5.1).

The estimation was carried out through multiple linear regression analysis. The best results were achieved when the 14 larger markets (334 monthly passengers or more) and the 19 smaller markets (176 monthly passengers or less) were dealt with separately. The regression equations obtained were as follows:

- Larger markets:

$$q_m = -10.00\,p_m - 7.71 c_m^P + 50.47\,P_j P_k + 38.10\,i_j i_k + 677.68 Y_{PDL_m} \left(R_{adj}^2 = 0.89\right) \quad (5.11)$$

Table 5.3 - Maximum round-trip airfares per market under PSO requirements (2009)

Market	PDL	TER	HOR	SMA	SJZ	PIX	FLW	GRW	CVU
PDL	-	158	158	92	158	158	158	158	158
TER	158	-	153	158	92	153	158	92	158
HOR	158	153	-	158	121	121	92	121	92
SMA	92	158	158	-	158	158	158	158	158
SJZ	158	92	121	158	-	121	158	121	158
PIX	158	153	121	158	121	-	158	121	158
FLW	158	158	92	158	158	158	-	158	46
GRW	158	92	121	158	121	121	158	-	158
CVU	158	158	92	158	158	158	46	158	-

Table 5.4 - Minimum number of flights and seats under PSO requirements and current number of flights (September 2009)

Flight leg	PSO requirements			Current number of flights	Flight time (min)
	Number of flights	Number of seats	Seats/ flight		
PDL - TER	22	2590	58,9	25	50
PDL - HOR	11	1270	57,7	14	50
PDL - SMA	10	1200	60,0	12	40
PDL - SJZ	3	330	55,0	5	90
PDL - PIX	7	780	55,7	8	60
PDL - FLW	2	190	47,5	3	30
TER - HOR	11	1320	60,0	12	60
TER - SJZ	8	820	51,3	9	40
TER - PIX	7	780	55,7	7	30
TER - FLW	2	190	47,5	2	30
TER - GRW	7	700	50,0	10	40
HOR - FLW	5	380	38,0	5	50
HOR - CVU	3	60	10,0	3	50
FLW - CVU	2	40	10,0	2	10

where: q_m is the number of passengers in market *m*, p_m are the airfares in market *m*, c^P_m are the passenger time costs in market *m*, P_j and i_j are the population (thousands) and the income per capita (EUR/inh.) in island of airport *j*, respectively; and Y_{PDL_m} is dummy variable for the presence of PDL in market *m*.

– Smaller markets:

$$q_m = -0.33\, p_m - 0.38 c_m^P - 3.28 i_j i_k - 41.97 Y_{CVU_m} - 79.03 Y_{Boat_m} \left(R^2_{adj} = 0.86 \right) \quad (5.12)$$

where: Y_{CVU_m} is a dummy variable for the presence of CVU (smallest airport) in market *m* and Y_{Boat_m} is a dummy variable for the existence of regular boat services competing with air services in market *m*.

More information on the results of the regression analysis is provided in Table 5.5.

Table 5.5 - Regression analysis of the demand function

Variables	Larger markets			Smaller markets		
	Coefficient	t-stat	p-value	Coefficient	t-stat	p-value
Population	50,47	9,67	0,00	-		
Income per capita	38,10	7,19	0,01	3,28	4,10	0,11
Airfares	-10,00	-3,79	0,43	-0,33	-3,11	0,77
Passenger time costs	-7,71	-2,39	4,06	-0,38	-1,88	8,05
Presence of PDL	677,68	3,64	0,54	-		0,00
Presence of CVU	-	-	-	-41,97	-2,05	5,99
Existence of Boat connection	-	-	-	-79,03	-3,28	0,55

5.4.2 Network-wide Results

The comparison between the current network and the optimum networks (with no-limit and with a 3-hour limit on maximum waiting time) was made at the network level with respect to the following indicators: total social costs, amount of public subsidies, airline costs, passenger time costs, airfares, aircraft fleet, number of flights, average load factor, number of connecting passengers, and average and maximum waiting time. The values obtained for these indicators are shown in Tables 5.6 and 5.7.

Table 5.6 - Costs, subsidies, and airfares for the current and the optimum networks

Network	Total Social Cost		Airline Operating Costs		Passenger Time Costs		Public Subsidies		Airfares	
	Value	Var. %	Value	Var. %	Value	Var. %	Value	Var. %	Value	Var. %
Current	163640	-	77116	-	9407	-	79792	-	74441	-
Optimum (No-limit)	152048	-7.1	65650	-14.9	9282	-1.3	74474	-6.7	68292	-8.3
Optimum (3-hour limit)	155817	-4.8	69865	-9.4	8836	-6.1	78170	-2.0	68811	-7.6

Table 5.7 – Fleet, number of flights, load factor, number of connecting passengers, and waiting time for the current and the optimum networks

Network	Fleet (DH2+DH4)	Number of Flights	Load Factor	Connecting Passengers		
				Number	Waiting Time (min)	
					Average	Maximum
Current	2 + 4	42	51,9%	114	47,7	495
Optimum (No-limit)	2 + 3	40	62,1%	133	46,8	390
Optimum (3-hour limit)	3 + 4	41	62,0%	130	33,8	210

For the current network, the total social costs are 163,640 EUR per day, corresponding to 42 flights with an average load factor of 51.9 percent. The amount of public subsidies needed to finance the network is 79,792 EUR (per day). The entire fleet operated by SATA (6 aircraft) is needed to run the network. Total airfares are equal to 74,441 EUR, airline operating costs sum to 77,116 EUR, and passenger time costs are 9,407 EUR. The percentage of connecting passengers is 7.8 percent (114 in 1,454 passengers), their average waiting time is 47.7 minutes, and the maximum waiting time is 495.0 minutes (PIX-TER-HOR). With this network, 12 passengers cannot reach their destination on the same day of departure even with two stops (the corresponding waiting time costs are not reflected in the value of the indicators).

If no limit is placed on the maximum waiting time, the total social costs of the optimum network are 152,048 EUR (a 7.1 percent decrease with respect to the current network). This is quite a significant decrease because approximately half of these costs – the airline ground and system operating costs – were assumed to be fixed. The number of flights drops to 40 and the average load factor increases to 62.1 percent. The amount of public subsidies decreases 6.7 percent to 74,747 EUR. The optimum network can be operated with 5 aircraft – 3 DH2 and 2 DH4 – instead of the current 6. Total airfares decrease by 8.3 percent to 68,292 EUR, airline operating costs decrease by 14.9 percent to 65,650 EUR, and passenger time costs decrease by 1.3 percent to 9,282 EUR. The percentage of connecting passengers is 9.1 percent, their average waiting time decreases to 46.8 minutes (-1.7 percent), and the maximum waiting time is 390 minutes (GRW-TER-PDL-SMA). All passengers can reach their destination on the same day of departure.

When the waiting time is limited to a maximum of 3 hours (for each stop), the total social costs of the optimum network are 155,187 EUR (-4.8 percent). As one should expect, these costs are higher than when no waiting time limit is considered, but still clearly lower than for the current network. The percentage of connecting passengers is 8.9 percent, larger than when no limit is placed on waiting time, but the average waiting time is reduced to 33.8 minutes (-29.1 percent) and the maximum waiting time is 210 minutes (PIX-PDL-FLW-CVU). In relation to the current network, the amount of public subsidies decreases by 2.0 percent to 78,170 EUR, total airfares decrease by 7.6 percent to 68,811 EUR, airline operating costs decrease by 9.4 percent to 69,865 EUR, and passenger time costs decrease by 6.1 percent to 8,836 EUR. The number of flights drops to 41 and the load factor increases to 62.3 percent. The network needs 7 aircraft to be operated (3 DH2 and 4 DH4), that is, one DH2 in addition to the aircraft currently being used (the costs of these aircraft were taken into account in the computation of airline operating costs).

5.4.3 Airport-specific Results

Network results show that the air transportation network of the Azores can be improved. However, this analysis does not allow the detection of possible negative effects specific to some airports/islands. To overcome this, we now examine how the optimum networks would impact the various islands of the archipelago, focusing on the following items: total number of daily flights, airfares, and waiting time of connecting passengers.

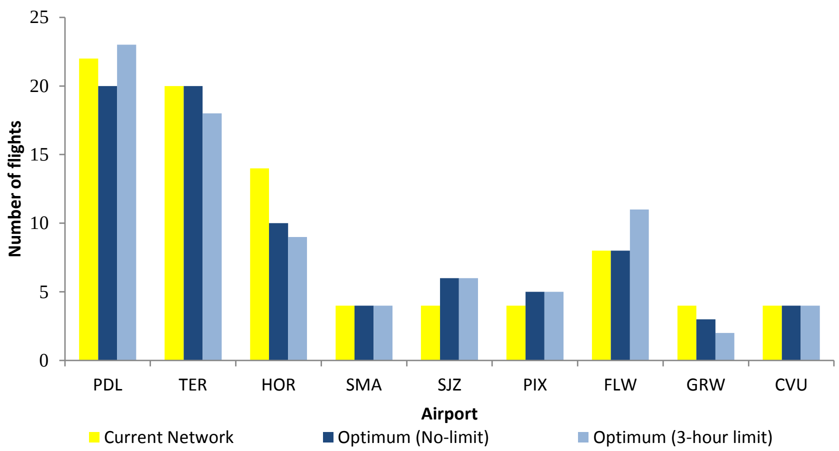

Figure 5.5 - Number of flights per airport for the current and optimum networks

With respect to the total number of daily flights serving each airport (thus, each island), changes are quite meager. As it can be seen in Figure 5.5, SMA, SJZ, PIX, FLW, and CVU do not lose any flights both when there is no limit on the waiting time faced by connecting passengers and when there is a limit of 3 hours. In contrast, TER and HOR stay at most with the same number of flights, and GRW loses flights in both cases. Finally, PDL loses two flights in the first case (no limit) and gains one in the second.

The airfares decrease on average for the optimum networks, but increase in some markets. It can be seen in Figure 5.6 that, in general, the number of markets that become less expensive is larger than the number of markets that become more expensive. This is particularly true with respect to GRW, where airfares decrease for all markets but one. In contrast, airfare increases affect 5 of the 6 markets involving CVU, the airport of the smallest island. As shown in Table 5.8, airfare changes can be rather substantial, with decreases above 60 percent in 5 markets (HOR-GRW, SJZ-PIX, HOR-SMA, SJZ-FLW, PIX-GRW) and increases above 60 percent in 3 markets (FLW-CVU, TER-CVU and HOR-CVU). These large changes can essentially by explained by two main reasons: the current amount of public subsidies per passenger is considerably higher (or lower) in some islands than in others, meaning that the airfares are relatively very low (or high); the travel times increase (decrease) more for some islands than for others, making the passengers from/to these islands more (less) willing to pay for their flights.

In relation to the waiting time of connecting passengers, the optimum networks show improvements from the current network, especially when the waiting time is limited to 3 hours (Table 5.9). The first reason is because there is no underserved demand (i.e. passengers that cannot reach their destinations on the same day of departure).

Table 5.8 - Round-trip airfares per market for the optimum network: value in EUR (upper triangle) and variation with respect to the current network (lower triangle)

Markets	PDL	TER	HOR	SMA	SJZ	PIX	FLW	GRW	CVU
PDL	-	130,0	141,5	77,4	148,3	178,3	157,6	163,1	227,0
TER	-17,9	-	143,2	216,7	95,9	142,5	151,5	81,9	264,1
HOR	-10,6	-6,7	-	49,2	111,7	144,2	83,5	20,7	148,4
SMA	-15,5	36,8	-69,0	-	177,3	67,7	168,0	120,5	168,8
SJZ	-6,4	4,8	-7,8	12,0	-	34,5	52,6	55,0	-
PIX	12,5	-7,1	19,1	-57,2	-71,5	-	188,7	45,8	99,1
FLW	-0,5	-4,4	-8,8	6,0	-66,8	19,1	-	130,7	89,4
GRW	2,9	-10,5	-82,9	-24,0	-54,6	-62,2	-17,5	-	-
CVU	43,3	66,7	62,2	6,5	-	-37,4	96,3	-	-

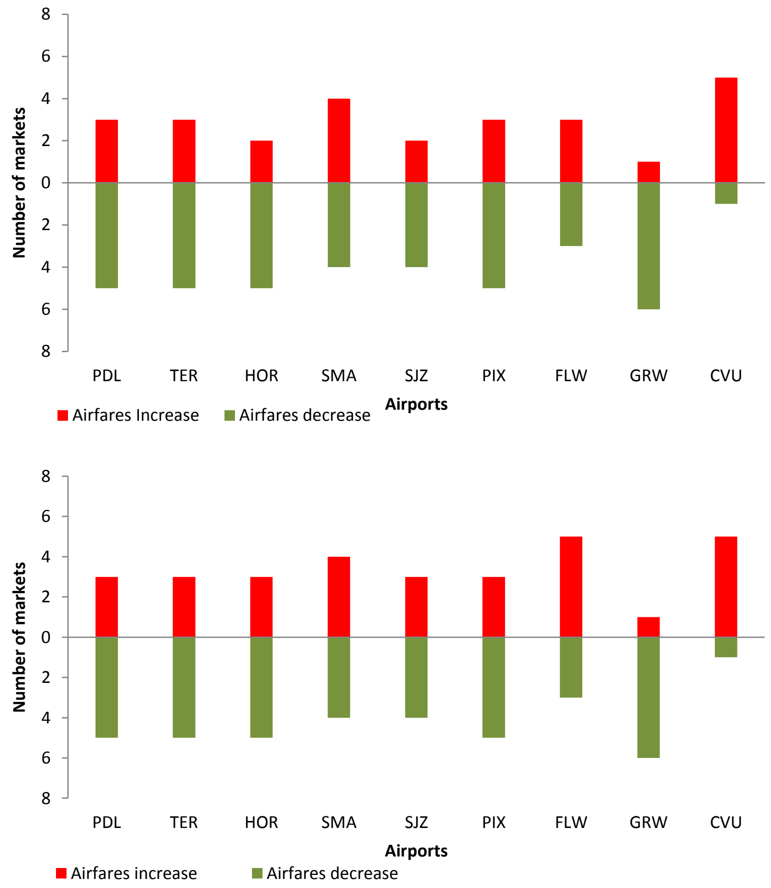

Figure 5.6 - Number of markets with airfare increase and decrease per airport when there is no waiting time limit (top) and when waiting time is limited to 3 hours (bottom)

In addition to this, when no limit is placed on the waiting time, the maximum waiting time decreases in all airports, except PDL and CVU, with the largest reductions in HOR and TER. In this optimum network, average waiting time increases at five airports, but it increased by more than 20 percent only at SMA and CVU. In contrast, it decreased at HOR and GRW by more than 20 percent. When the waiting time is limited to 3 hours, the results are significantly better than in the current network. The maximum waiting time decreases at least 57 percent at seven airports and only at CVU is the maximum waiting time increased, and by less than 8 percent. The average waiting time increases at three airports (PDL, TER, and CVU), while the other six airports have reductions of at least 35 percent.

Table 5.9 - Number of connecting and not-served passengers and average and maximum waiting time per island for the current and optimum networks

Indicator	Network	Airport								
		PDL	TER	HOR	SMA	SJZ	PIX	FLW	GRW	CVU
Number of connecting passengers	Current	38	28	18	15	12	8	45	50	14
	Optimum (No-limit)	45	28	18	18	16	18	50	54	18
	Optimum (3-hour limit)	38	28	22	18	16	12	50	54	22
Average waiting time	Current	25	29	68	68	70	85	42	58	41
	Optimum (No-limit)	26	28	51	104	58	101	47	25	68
	Optimum (3-hour limit)	33	38	33	43	26	30	27	35	44
Maximum waiting time	Current	75	435	495	435	405	495	375	465	195
	Optimum (No-limit)	150	195	165	390	345	360	360	390	300
	Optimum (3-hour limit)	75	105	150	180	135	210	105	135	210
Underserved passengers	Current	0	0	0	2	4	5	4	3	6
	Optimum (No-limit)	0	0	0	0	0	0	0	0	0
	Optimum (3-hour limit)	0	0	0	0	0	0	0	0	0

5.4.4 Sensitivity Analysis

In order to assess the variability of results, a sensitivity analysis was performed with respect to four important parameters: demand targets, maximum load factor per leg, value of time, and stoppage costs. For the demand targets we tested values of -20, -10, -5, +5, +10, and +20 percent of the reference values (Table 5.2). For the maximum load factor per leg, two alternatives were analyzed: 80 and 100 percent (instead of 90 percent). For the value of time we used three values: 2.5, 7.5, and 10.0 EUR per hour (instead of the reference value of 5.0 EUR per hour). Finally, the stoppage costs were set at 20 and 50 percent of the airline operating costs (instead of 33 percent). The analysis was carried out considering no limit on the maximum waiting time of connecting passengers and the following indicators: total social costs, amount of public subsidies, airline operating costs, passenger time costs, and aircraft fleet. The results obtained for the sensitivity analysis are displayed in Table 5.10.

In response to the change in demand targets, as expected, the amount of public subsidies per day increases as the number of passengers increases (Figure 5.7). When the number of passengers decreases by 20 percent, the amount of public subsidies drops by 27.7 percent with respect to the current network, and when it increases by 20 percent the subsidies grow by 23.8 percent. The total social costs also increase, but at a much smaller rate, and do not reach the costs for the current network even when the demand increases by 20%. Airline operating costs follow approximately the same pattern as total social costs. Passenger time costs grow quickly, faster than the demand. The fleet necessary to run the network varies between 4 and 6 aircraft. For levels of passengers between -10 and +10 percent of the reference values, the optimal fleet does not change.

In contrast, it reduces to 4 aircraft only with 20 percent fewer passengers (2 DH2 and 2 DH4) and increases to 6 aircraft (3 DH2 and 3 DH4) with 20 percent more passengers.

Table 5.10 - Fleet, costs, subsidies, and airfares for the optimum network using different values of demand targets, maximum load factor, values of time, and stoppage costs

Network			Total Social Cost		Airline Operating Costs		Passenger Time Costs		Public Subsidies		Fleet (DH2+DH4)
			Value	Var. %	Value	Var. %	Value	Var. %	Value	Var. %	
Current		-	163640	-	77116	-	9407	-	79792	-	2 + 4
Optimum	Demand Target (%)	-20	144146	-11.9	59168	-23.3	7861	-16.4	57660	-27.7	2 + 2
		-10	146297	-10.6	61399	-20.4	8138	-13.5	62971	-21.1	2 + 3
		-5	149056	-8.9	64060	-16.9	7880	-16.2	68620	-14.0	2 + 3
		0	152048	-7.1	65650	-14.9	9282	-1.3	74474	-6.7	2 + 3
		+5	156080	-4.6	69309	-10.1	9654	2.6	81870	2.6	2 + 3
		+10	157072	-4.0	69102	-10.4	10853	15.4	86748	8.7	2 + 3
		+20	158044	-3.4	67643	-12.3	12284	30.6	98817	23.8	3 + 3
Optimum	Load Factor (%)	100	149414	-8.7	62056	-19.5	10241	8.9	71316	-10.6	3 + 2
		90	152048	-7.1	65650	-14.9	9282	-1.3	74474	-6.7	2 + 3
		80	157892	-3.5	71585	-7.2	9190	-2.3	80191	0.5	2 + 3
Optimum	Value of Time (EUR/h)	10	160055	-2.2	142702	85.0	17353	84.5	79582	-0.3	2 + 3
		7.5	155835	-4.8	141644	83.7	14192	50.9	76580	-4.0	2 + 3
		5	152048	-7.1	65650	-14.9	9282	-1.3	74474	-6.7	2 + 3
		2.5	147159	-10.1	142612	84.9	4547	-51.7	71124	-10.9	2 + 3
Optimum	Stoppage costs (%)	20	149610	-8.6	63853	-17.2	8641	-8.1	72055	-9.7	2 + 3
		33	152048	-7.1	65650	-14.9	9282	-1.3	74474	-6.7	2 + 3
		50	152493	-6.8	66373	-13.9	9004	-4.3	75711	-5.1	2 + 3

Also as expected, the amount of public subsidies increases as the load factor decreases. When the maximum load factor per leg is 100 percent, the gain with respect to the current network is 10.6 percent, and when it is 80 percent, there is a loss of 0.5 percent. The same occurs, though in smaller scale, with the total social costs and the airline operating costs. In contrast, passenger time costs increase with the maximum load factor per leg because there are fewer flights (thus waiting times are longer). The optimum fleet is 3 DH2 and 2 DH4 when the maximum load factor per leg is 100 percent instead of 2 DH2 and 3 DH4 when it is 90 or 80 percent.

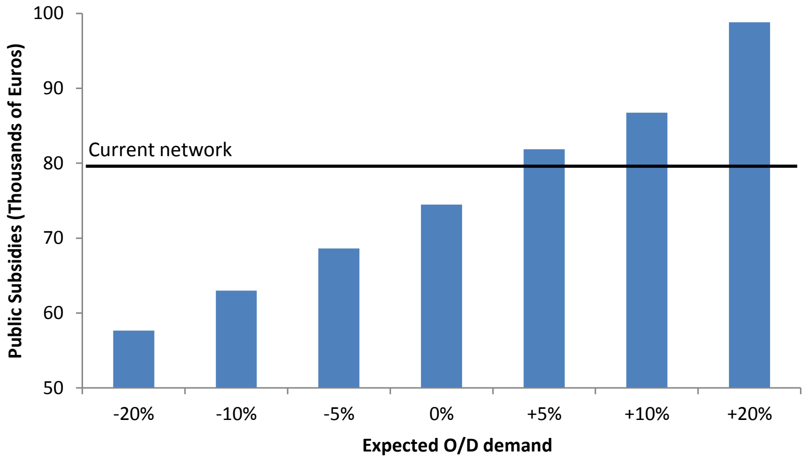

Figure 5.7 - Amount of public subsidies for different demand targets

Changes in the value of time affect directly the passenger time costs. These costs vary almost proportionally with the value of time, at approximately the same rate (they almost double when the value of time doubles). In terms of total social costs and of the amount of public subsidies, the results point to reductions on the same scale of the ones obtained in the optimum networks when comparing to the current network, even when the value of time is 10 EUR per hour. The impact of value of time changes on airline operating costs is minor, and on the aircraft fleet is nil.

Finally, changes in the stoppage costs do not have a strong impact on results. The total social costs, the airline operating costs, and the amount of public subsidies all increase with the increase of the stoppage costs, but at a slower rate. For all stoppage cost values, the total social costs and the airline operating costs are lower than those obtained with the current network. The same occurs with the amount of public subsidies, which, in relation to the current network, decrease 5.1 and 9.7 percent when stoppage costs are 50 and 20 percent of flight costs, respectively. The optimal fleet does not change for the range of stoppage costs considered (2 DH2 and 3 DH4).

5.4.5 Computational Effort

The optimization model was solved on a Quad Core processor with 4GB of RAM using the optimizer version 22.01.04 of the commercial software Xpress (FICO, 2011). The model involved more than 5,000 integer variables and 150,000 real variables. The computation time without limiting the passenger waiting time was 88.1 minutes – the LP relaxation took 0.6 seconds, the first feasible integer solution was obtained after 1.7 minutes, and the 10-percent optimality gap was reached in 10.7 minutes. Considering all model runs, the computation time varied between 2.7 minutes (3-hour maximum waiting time and 80% maximum load factor) and 154.8 minutes (demand targets equal to -20% of the reference values and maximum load factor of 80%). The average computation time was 52.4 minutes. The computation times required to solve this case study seem to be reasonable for an optimization model that is to be used in processes that are repeated only once every three years.

5.5 Conclusions

In this chapter, a decision approach have presented aimed to assist governments (aviation authorities) in the establishment of PSO requirements for the air transportation networks of low-demand regions. The approach is based on an integrated flight scheduling and fleet assignment model and determines the air transportation network that minimizes the total social costs of satisfying a given origin/destination (O/D) demand, as well as the amount of public subsidies necessary to finance the network.

The application of the decision approach to the network of Azores (Portugal), one of the largest networks fully operated under a PSO system, demonstrates its practical usefulness. Indeed, the results of the application clearly indicate that, overall, the network of the region could be better for all stakeholders – passengers, airline, and government (this, of course, assumes validity of our assumptions and correctness of our data). It is, however, worth noting that the impacts on the various islands would be quite different, and some could be worse off if the approach is implemented (e.g., the airfares paid for flights involving Corvo, the smallest island, would increase, in some cases substantially).

The decision approach presented in this chapter is, I believe, a valuable addition to the air transportation literature. Indeed, the literature on low-demand networks is quite meager (though growing quickly), and up to now has not focused on the kind of operational issues we have addressed here. However, we must recognize that it has some limitations. For example, the approach does not distinguish between passengers (residents, students, retired people), and such distinction often occurs in these types of networks. Also, it does not take into account the cost of airports, which, in this type of network, are publicly owned (like in the Azores). The future work in this area will aim at overcoming these limitations.

Chapter 6

Multiple Perspectives on Air Transportation Networks in Sparsely Populated Regions with an application to Norway

6.1 Introduction

After deregulation of the airline markets, the freedom to choose where and how frequently to fly led to an under supply on some of the thinner airline markets. If regional government policy encourages and supports communities in remote regions such as Alaska, Northern Canada, the Canary Islands, Northern Norway and the interior of Australia, it may be necessary to subsidize the air transport network. Designing a publicly supported network that provides a reasonable level of accessibility at a competitive price is not a simple task. A welfare based flight schedule and fleet assignment optimization model (WFSFA) is developed in this research in order to determine a network configuration that minimizes the overall social costs of the air transportation network. A social welfare computation based on the network solution evaluates passenger, airline, airport and government welfare which permits a comparison across different levels of accessibility and their related subsidy requirements.

Public support systems such as the European Union's public service obligation (PSO), Australia's regional aviation access program (RAAP) and North America's essential air services (EAS) are one of the direct consequences of liberalization and deregulation of the airline industry (WILLIAMS, 2005). Details and comparisons of the PSO and the EAS systems are discussed in REYNOLDS-FEIGHAN (1995b), SANTANA (2009), and, more recently, in BRAATHEN (2011). The EAS was initiated after the Deregulation Act of 1978 (US DOT, 2009; MENDES-METRASS and DE NEUFVILLE, 2010) and the PSO system was launched in 1992 (CEC, 1992a; CEC, 1992b; CEC, 1992c) as part of the air transportation liberalization process in Europe (REYNOLDS-FEIGHAN, 1995a; WILLIAMS, 2005). According to European Union policy, a government can impose a PSO between any airport in its territory and any airport in the European Union if that route is considered to be crucial for economic and social development of the region (CEC, 2008). Air transportation services are necessary to provide remote settlements with access to essential services such as healthcare and education, and the country or regional capital, as well as promotion of the local economy and for purposes of national cohesion (HALPERN and BRAATHEN, 2010). As a result, by 2010, more than 260 routes in ten different European countries were operated according to the PSO system (CEC, 2010). The awarding of PSO routes involves a competitive tender process in which airlines bid to operate the routes while satisfying the requirements set by the government. The winning airline operates the route as a monopoly and receives a public subsidy to do so. PSO requirements usually impose a specified level of service as a function of a minimum number of flights per leg, a minimum aircraft configuration (aircraft propulsion and minimum number of seats), maximum or average fare levels, and earliest/latest departure/arrival times.

Despite the common legal framework in Europe, countries have adopted different strategies and policies in relation to PSO networks. The variety of policies and requirements between countries has helped to create barriers to entry which reduce the competitiveness of the tender process leading to an increase in costs over time (WILLIAMS, 2005). According to SANTANA (2009), airlines that operate networks under subsidized programs have higher operating costs than airlines operating in competitive networks. Barriers to entry are generally caused by three factors. First, the PSO routes are awarded for three years which does not give new entrants sufficient time to organize the initial investment. Second, airlines have a very short period (very often only one month) to prepare for the operations once they win the tender. Third, aircraft specifications are often highly restrictive, which reduces the number of airlines capable of meeting the PSO requirements. For example, Norway requires (for most of the PSO routes) a pressurized aircraft with a minimum of 30 seats capable of operating at airports with runways of less than 1,000 meters. To overcome some of these problems, WILLIAMS (2005) proposes that the PSO cycle should be extended to five years with additional time between the end of the tender process and the beginning of operations. Moreover, according to REYNOLDS-FEIGHAN (1995b), a centralized European program may enhance efficiency and public accountability, namely by harmonizing the size of communities to be served, setting a minimum distance to the nearest central hub, and considering alternative means of transport.

The literature to date discussing subsidized air transportation networks have focused on the economic and societal impact of these networks on populations, regions and airlines (GRAHAM, 1998; METRASS-MENDES et al., 2011; LIAN, 2010) and on the legal framework (REYNOLDS-FEIGHAN, 1995a; SANTANA, 2009; BRAATHEN, 2011). To the best of our knowledge, the first integrated flight schedule and fleet assignment (IFSFA) operational model developed for subsidized networks is presented in Pita et al. (2012). Schedule design and fleet assignment problems have been extensively discussed in the literature due to their importance for the airline planning process. For the flight scheduling problem readers are referred to ERDMANN et al. (2001), BARNHART et al. (2002), and YAN and CHEN (2007) and for the fleet assignment problem ABARA (1989), HANE et al. (1995), and DUMAS et al. (2009). In the last decade, a number of papers have analyzed the two issues simultaneously through integrated models. See for example DESAULNIERS et al. (1997), REXING et al. (2000), LOHATEPANONT and BARNHART (2004), YAN et al. (2008), and SHERALI et al., (2010).

This research extends the approach discussed in Chapter 5 in four main directions. First, airport costs and revenues are endogenized in the optimization model and analyzed in the social welfare analysis. Second, passenger travel time preferences, measured by schedule delay, are included in the optimization model and the subsequent passenger welfare analysis. Third, passenger demand and airfares are endogenized in the optimization model permitting an analysis of the impact of airfares on the service provided. Fourth, a social welfare computation to analyze the trade-offs across multiple scenarios is developed, based on the optimization model outputs. It includes a passenger, airline, airport, and government welfare analysis in order to compare various scenarios from multiple perspectives.

The chapter is organized as follows. The mathematical modeling of the WFSFA optimization model and social welfare analysis are presented in Section 6.2. A case study of the Norwegian regional air transportation network, mainly operated under PSO conditions, is described in Section 6.3. Section 6.4 analyzes the results of the WFSFA model and the social welfare analyses with respect to Norway, highlighting the improvements that could be attained by all stakeholders. Final remarks, conclusions, and guidelines for future research are addressed in Section 6.5.

6.2 The welfare-based flight schedule and fleet assignment approach

This research develops an approach design PSO networks which balances the trade-offs across the different actors being served by the network, based on the WFSFA optimization model. The assessment of the social welfare outcome of the model is important for government agencies whose goal is to make the best use of public resources and, simultaneously, maintain an acceptable level of service for passengers. The level of service is measured by flight frequency, itinerary types and maximum waiting time between flight legs. The main research question can be formulated as follows:

> *"How should an air transportation network operated as a public service be organized such that total network costs are minimized?"*

Four different, and sometimes conflicting, objectives need to be taken into account by the government, or the aviation authority on its behalf, when setting PSO requirements. First, the utility function of passengers minimizes total trip costs, which is a function of airfare, flight frequency, number of legs in the itinerary, and total travel time required to complete the journey. Second, the frequently publicly-owned airport management should be encouraged to operate efficiently as a function of operating costs and revenues. Third, the monopolistic airline carrier operates the PSO routes by maximizing their profits given the minimum level of service requirements set by the aviation authority. Through the tender process, the airlines are also encouraged to minimize the level of subsidies requested. Fourth, government agencies spending public funds should consider the social benefits, territorial cohesion, and economic development that such investments may achieve.

In general, passengers prefer lower travel costs, or in other words, to have a convenient flight itinerary at an affordable price. Those two parameters depend mainly on the passenger type and trip purpose. Typically, two passenger types are considered as function of the purpose of the trip: business and leisure. Business passengers tend to be more time-sensitive than price-sensitive especially in short-haul markets such as PSO markets (ADLER and GELLMAN, 2012). Hence, business passengers place greater value on higher flight frequency and more direct routes in order to minimize schedule delay and the number of required connections. Leisure passengers tend to be more price-sensitive than time-sensitive and therefore are more willing to accept higher schedule delays and multi-leg itineraries (BORENSTEIN and NETZ, 1999; NOLAN et al., 2005). Consequently, business passengers tend to have higher values of time. The approach endogenizes the passenger travel cost in the optimization process and estimates the trip utility per passenger type and per market in the social welfare analysis. Travel cost is a function of airfares and time costs, including the time spent on board, waiting between connections, and schedule delay.

On PSO routes, the tender mechanism often sets maximum airfares, which takes into account a given origin-destination (O/D) demand level. The government body that regulates prices is aware that lower fares are likely to stimulate demand but equally likely to increase the level of subsidies requested by the airlines. A balance is therefore sought between passenger demand, airfares and subsidies considering the budget limitations of the PSO service necessary to support regional policy directions.

Passenger time costs are directly related to the passenger value of time, thus with the trip purpose and passenger type (ADLER, 2005; JORGE-CALDERÓN, 1997). Three elements are considered within the passenger disutility function: on-board time costs, waiting time costs between flight legs on a connecting itinerary, and schedule delay costs. Waiting time cost covers the time spent at the hub airports between flight legs for passengers travelling on multi leg itineraries. Schedule delay is the difference between the passengers' preferred travel time and the time when a flight is available (RYERSON and HANSEN, 2010). The passengers' preferred travel time is difficult to ascertain because flight time choices are related to existing schedules. According to BREY and WALKER (2011a), the 9 am and 6 pm peaks are the most important of the day, followed by 10 pm, noon, and 7 am. For the outbound flights, BREY and WALKER

(2011b) stated that business passengers show a much stronger peak in the morning than leisure passengers. It is therefore, reasonable to assume that business passengers are more willing to travel outbound in the early morning and return in the late evening than non-business (leisure) passengers, reflecting the higher value of time for business passengers.

Frequently, PSO routes connect a local airport to a central airport, which also serves numerous commercial flights, hence may not depend on PSO flights to achieve a break-even point. The local airports, however, are served partly (or totally) by flights operated under PSO conditions and may generate deficits if the revenues are insufficient to cover their costs. When the entire airport system is organized under a single owner, usually the government, then the larger airports tend to cross-subsidize the smaller regional airports. Alternatively, a direct subsidy will be required from the government or local authorities.

According to ADLER et al. (2012), the break-even point of small regional airports increased from 400,000 passengers on average in 2002 to 1.3 million by 2009, in part due to substantial security investments that have been imposed as a result of the 9/11 terrorist attacks. The results of an efficiency analysis of 83 European airports suggest that airport groups are 6 percent less efficient than stand-alone entities because they fail to encourage cost efficiency and entrepreneurship, probably in part due to soft budget constraints imposed on management. In this approach, we assume that airports are publicly owned and that the government is interested in minimizing the subsidies granted to local airports through either a reduction in airport operating times or an increase in revenues.

Regardless of whether they operate PSO routes or not, private airlines maximize profits in part by ensuring operational efficiency. On PSO routes, airlines have substantially less flexibility to change aircraft types, flight frequencies and market seat capacity because such parameters are usually defined by the PSO requirements. Therefore, a fleet planning and assignment model which will develop a reasonable schedule to be defined in the tender may aid in setting PSO requirements that reduce costs, hence minimize the subsidy level requested by the airlines.

Finally, government agencies in charge of regulating the PSO routes need to balance the requirements of the various stakeholders including the airports, airlines and passengers. An efficient PSO system will balance airline and airport operating costs, level of service provided to passengers, and the subsidies granted to airlines and airports thus minimizing public expenditure.

Our approach is to apply the WFSFA model and the social welfare analyses to highlight the trade-offs, based on multiple objectives, and consequently support government agencies in developing an efficient PSO mechanism. It should be underlined that this style of formulation is a partial transport equilibria outcome in which only direct operating costs and revenues are considered. Therefore, indirect or induced costs or revenues generated by air transportation to/from remote regions are not taken into account, including their impact on the local economy or the environment.

6.2.1 Optimization Model

Integrated flight schedule and fleet assignment models have been published in the literature mostly from the airline perspective, where the objective is to maximize profits

(LOHATEPANONT and BARNHART, 2004; YAN et al., 2008; SHERALI et al., 2010). The main differences between that approach and the welfare based flight schedule and fleet assignment model (WFSFA) are the following: (1) the overall objective is to minimize social cost instead of maximizing airline profit; (2) passengers' time costs and airport operating costs are endogenized because they represent important social costs; (3) the network is operated under a monopolistic rather than competitive regime; (4) maximum airfares are regulated by the PSO requirements rather than being a result of market characteristics; and (5) a minimum level of service (e.g., number of non-stop flights, maximum waiting time between flight legs) is guaranteed for each leg and/or market.

The WFSFA model is applied to a day of operations divided into time-periods (e.g., 15 or 30 minutes) and to itineraries of up to 2-stops (i.e., 1, 2 or 3 flight legs), which represent the vast majority of itineraries. We also assume that passengers only travel in a 2-stop itinerary if no feasible itinerary is available with a higher level of service (non-stop or 1-stop), which reflects the influence of level of service on passenger choice (COLDREN et al., 2003).

The notation required for the optimization model is presented in Table 6.1.

The WFSFA objective (6.1) minimizes the social cost of the air transportation system which is the difference between operating costs and revenues. The first term represents the airline operating costs as the sum of flight costs and off-base costs. The flight costs are a function of the flight leg (first element) and the off-base costs (second element) which include apron charges whenever an aircraft is not parked at the base of the airline. The second term represents the airport variable operating costs, which includes

Table 6.1 – Optimization model notation

Sets

$\boldsymbol{A} = \{1, \ldots, A\}$ - set of airports indexed by j and k

$\boldsymbol{F} = \{1, \ldots, F\}$ - set of aircraft types indexed by f

$\boldsymbol{I} = \{1, \ldots, I\}$ - set of itineraries indexed by i

$\boldsymbol{L} = \{1, \ldots, L\}$ - set of flight legs indexed by l

$\boldsymbol{L^{O}_{jt}} = \{1, \ldots, L\}$ - set of outbound flight legs from airport j in time period t indexed by l

$\boldsymbol{L^{I}_{jt}} = \{1, \ldots, L\}$ - set of flight legs arriving at airport j in time period t indexed by l

$\boldsymbol{L^{C}_{t}} = \{1, \ldots, L\}$ - set of flight legs that pass the count time t indexed by l

$\boldsymbol{L_{jk}} = \{1, \ldots, L\}$ - set of flight legs between airports j and k

$\boldsymbol{M} = \{1, \ldots, A\}$ - set of origin-destination markets indexed by m

$\boldsymbol{T} = \{1, \ldots, T\}$ - set of time windows indexed by t

---

Parameters

c^{V}_{lf} - flight costs for an aircraft of type f to fly leg l ($per flight)
c^{O}_{jft} - off-base costs of having an aircraft of type f parked at airport j ($per aircraft and time window)
c^{B}_{i} - on-board time cost for a passenger in itinerary i ($per passenger)
c^{W}_{i} - waiting time cost for a passenger in itinerary i ($per passenger)
c_{Aj}- variable airport cost per hour of operation ($/hour)
c_{SDm} - schedule delay cost for a passenger on market m ($/minute per passenger)
l_l - maximum load factor for flight leg l
s_f - capacity of an aircraft of type f
δ^{l}_{i} - parameter equal to 1 if flight leg l belongs to itinerary i, and 0 otherwise
d_m - number of passengers for OD market m
δ^{m}_{i} - parameter equal to 1 if itinerary i belongs to market m, and 0 otherwise
r_m - average revenue on market m ($per passenger)
r_{Cj} - average commercial revenue on international markets for airport j ($per passenger)
e_{dm} - price elasticity of demand on market m
d^{T}_{mt} - %age of the daily demand on market m with desirable travel time on time period t
M - auxiliary big number (for formulation purposes only)

Decision Variables

x_{lf} – number of flights by aircraft type f on leg l, which is the flight leg between airports jk that take off on time window t (binary variable)
y_{jft} – number of aircraft of type f that are ready to take off from airport j on time window t
q_i – number of passengers assigned to itinerary i
$q^{T}_{mtt'}$ – passengers on market m with desirable travel time on time period t and departure time on time period t'
n_f – number of aircraft of type f (integer variable)
v_{jk} – revenue variation per market (percentage)
z_{jh} – binary variable: 1 if airport j is open on hour h and 0 otherwise

---

employee, operating equipment, security, energy, and depreciation expenses as a function of the opening times of an airport. The third term corresponds to the passenger on-board time costs computed by multiplying the number of passengers per itinerary with the corresponding flight time cost (flight time multiplied by the value of time). The fourth term corresponds to the passenger waiting time costs between flight legs computed by the number of waiting passengers per itinerary multiplied by their value of time. The sixth term represents the schedule delay cost as a function of the difference between the most desirable travel time and the flight schedule multiplied by the number of passengers and schedule delay cost. Finally, the seventh term computes the airport non-aeronautical revenues including commercial, duty-free and parking revenues measured by the average commercial revenues per departing passenger multiplied by the number of passengers.

In the objective function, we do not consider aeronautical revenues including landing fees, security fees and passenger departing fees because they are simultaneously a cost to the airlines and revenue for the airports. Security fees are levied by various methods, per example they may be paid by the airline directly or they may be added to the airfare in form of a surcharge to passengers. Therefore, these costs are computed in the social welfare analysis but not in the optimization model.

Airfares are also omitted from the objective function as they represent a direct cost to the passengers and a source of revenue to the airlines and indirectly to the government via taxes. Airfare variation from the current average airfare per market is calculated in the demand function, hence impacts the number of passengers served.

$$
\begin{aligned}
\min C = & \sum_{l \in L} \sum_{f \in \boldsymbol{F}} c_{Vlf}\, x_{lf} + \sum_{j \in \boldsymbol{A}} \sum_{f \in \boldsymbol{F}} \sum_{t \in \boldsymbol{T}} c_{Ojf}\, y_{jft} \\
& + \sum_{j \in \boldsymbol{A}} \sum_{h \in \boldsymbol{H}} c_{A_j} z_{jh} \\
& + \sum_{i \in \boldsymbol{I}} c_{B_i} q_i + \sum_{i \in \boldsymbol{I}} c_{W_i} q_i \\
& + \sum_{m \in \boldsymbol{A}} \sum_{t, t' \in \boldsymbol{T}} c_{SD_m} (t' - t) q^{T}_{mtt'} \\
& - \sum_{i \in \boldsymbol{I}} r_{C_i} q_i
\end{aligned} \tag{6.1}
$$

Nine sets of constraints are included in the model. The balance, availability, and continuity constraints are standard constraints in the flight scheduling and/or fleet assignment model. In addition, new or modified constraints have been developed to consider specific aspects relevant to the subsidized networks.

The balance constraints (6.2) guarantee that daily departures and arrivals per airport and aircraft type are equal.

$$
\sum_{l \in \boldsymbol{L}^{\boldsymbol{O}}_{\boldsymbol{jt}}} x_{lf} = \sum_{l \in \boldsymbol{L}^{\boldsymbol{I}}_{\boldsymbol{jt}}} x_{lf}, \forall f \in \boldsymbol{F} \tag{6.2}
$$

Availability constraints (6.3) ensure that, for each aircraft type, the number of aircraft in use is equal to the available fleet.

$$
\sum_{j \in \boldsymbol{A}} y_{jft} + \sum_{l \in \boldsymbol{L}^{\boldsymbol{O}}_{\boldsymbol{jt}}} x_{lf} + \sum_{l \in \boldsymbol{L}^{\boldsymbol{C}}_{\boldsymbol{t}}} x_{lf} = n_f, \forall f \in \boldsymbol{F}, t \in \boldsymbol{T} \tag{6.3}
$$

The continuity constraints (6.4) ensure the aircraft flows per time period, aircraft type and airport. If necessary, constraints (6.5) ensure cyclical continuity.

$$
y_{jf,t-1} + \sum_{l \in \boldsymbol{L}^{\boldsymbol{I}}_{\boldsymbol{jt}}} x_{lf} - y_{jft} - \sum_{l \in \boldsymbol{L}^{\boldsymbol{O}}_{\boldsymbol{jt}}} x_{lf} = 0, \forall j \in \boldsymbol{A}, f \in \boldsymbol{F}, t \in \boldsymbol{T} \mid t > 1 \tag{6.4}
$$

$$y_{jfT} + \sum_{l \in \boldsymbol{L}_{jT}^{I}} x_{lf} - y_{jf1} - \sum_{l \in \boldsymbol{L}_{j1}^{O}} x_{lf} = 0, \forall j \in \boldsymbol{A}, f \in \boldsymbol{F} \quad (6.5)$$

The aircraft capacity constraints (6.6) ensure that the number of passengers does not exceed the available seats. The total passengers per flight account for all itineraries covering the relevant leg, including non-stop, 1-stop, and 2-stops journeys. To account for demand variability, the available number of seats may be limited using a maximum load factor below one (SWAN, 2002).

$$\sum_{f \in \boldsymbol{F}} l_l s_f x_{lf} \geq \sum_{i \in \boldsymbol{I}} \delta_i^l q_i, \ \forall l \in \boldsymbol{L} \quad (6.6)$$

The demand equation (6.7) aggregates demand per market with the number of passengers assigned to the itineraries of that market. Demand per market, the left hand side of the equation, is equal to the expected demand given the current average air fare multiplied by the demand variation due to a change in the average airfare per market. We consider demand elasticity per market to be fixed and given.

$$d_m \left(1 - e_{d_m} v_m\right) = \sum_{i \in \boldsymbol{I}} \delta_i^m q_i, \forall m \in \boldsymbol{M} \quad (6.7)$$

Equation (6.8) sets the number of hours airport j is open and requires the airport to be open whenever an aircraft movement is being served. M is the maximum number of daily hours that an airport can be open.

$$\sum_{l \in \boldsymbol{L}_{jh}^{O}} \sum_{f \in \boldsymbol{F}} x_{lf} + \sum_{l \in \boldsymbol{L}_{jh}^{I}} \sum_{f \in \boldsymbol{F}} x_{lf} \leq M z_{jh}, \ \forall j \in \boldsymbol{A}, h \in \boldsymbol{H} \quad (6.8)$$

Schedule delay per passenger and market is defined in equations (6.9) and (6.10). The right-hand side of equation (6.9) sets the number of passengers who prefer to travel in time period *t*, according to the demand distribution d^T_{mt}. The left-hand side distributes the demand according to departing times t'. Equation (6.10) distribute passengers with desirable travel time *t* departing in time period *t'* (left-hand side) to the corresponding itineraries (right-hand side).

$$d^T_{mt} d_m \left(1 - e_{d_m} v_m\right) = \sum_{t' \in \boldsymbol{T}} q^T_{mtt'}, \forall m \in \boldsymbol{M}, t \in \boldsymbol{T} \quad (6.9)$$

$$\sum_{t \in \boldsymbol{T}} q^T_{mtt'} = \sum_{i \in \boldsymbol{I_m}} q_i, \forall m \in \boldsymbol{A}, t' \in \boldsymbol{T} \quad (6.10)$$

Finally, x_{lf}, which describes the flight legs to be flown and the fleet required, and z_{jh}, which sets airport *j*'s opening hours, are binary variables while all other variables are continuous.

6.2.2 Social Welfare Analysis

The social welfare analysis calculates the airline profits (Π), passenger disutility (W_C) and airport surplus (W_G) (6.11) based on the results of the optimization model. We assume that, the marginal cost (m_C) of public funds is set exogenously and for the Norwegian case study equals 1.2 based on CALTHROP et al. (2010).

$$W = W_C + \Pi + m_C W_G \quad (6.11)$$

The passenger surplus is estimated by adapting the utility function presented in ADLER et al. (2010) (6.12) which combine total travel time, travel cost, and level of service.

$$W_{C_m} = \beta_0 + \beta_1 TTT_m + \beta_2 TP_m + \beta_3 FR_m, \forall m \in \boldsymbol{M} \quad (6.12)$$

where β_v weights the relative importance of parameters v={0,1,2,3}. TTT_m represents the total travel time in market m in hours obtained by aggregating the on-board time, the waiting time between flight legs and the schedule delay (6.13). TP_m represents the total price in market m defined in equation (6.14). FR_m represents the log of the minimum flight leg frequencies belonging to market m (6.15).

$$TTT_m = \sum_{i \in \boldsymbol{I_m}} FT_i q_i + \sum_{t,t' \in \boldsymbol{T}} (t'-t) q_{mtt'}, \forall m \in \boldsymbol{M} \tag{6.13}$$

$$TP_m = r_m \left(1 - e_{d_m} v_m\right) \sum_{i \in \boldsymbol{I_m}} q_i, \forall m \in \boldsymbol{M} \tag{6.14}$$

$$FR_m = \ln\left[\min\left(\sum_{l \in \boldsymbol{L_m}} \sum_{f \in \boldsymbol{F}} x_{lf}\right)\right], \forall m \in \boldsymbol{M} \tag{6.15}$$

where, r_m equals the average airfare in market m.

The airline surplus is defined as the difference between total airline revenues and operating costs (6.16). Revenues are the sum of airfares and other ancillary revenues (beverages, food and duty-free), without taxes. On PSO routes, the latter type of revenue tends to be very small and is not included in this analysis. In terms of costs, we need to consider direct operating costs, landing fees, and indirect costs. Operating costs are obtained from the results of the optimization model through equation (6.1). Landing fees depend on the airport and aircraft landing and take-off cycle and we assume that those values are known and fixed. Finally, indirect costs are usually estimated as a percentage of the operational costs. According to SWAN and ADLER (2006) and BELOBABA et al. (2009), indirect costs approximately equal the level of operating costs, although differences between airlines may be significant.

$$\Pi = \sum_{m\in \boldsymbol{M}} r_m (1-VAT)\left(1-e_{d_m} v_m\right)\sum_{i\in \boldsymbol{I_m}} q_i - \sum_{j\in \boldsymbol{A}}\sum_{f\in \boldsymbol{F}} c_{LF_{jf}} \sum_{l\in \boldsymbol{L_j}} x_{lf} - \alpha\left(\sum_{l\in \boldsymbol{L}}\sum_{f\in \boldsymbol{F}} c_{Vlf}\, x_{lf} + \sum_{j\in \boldsymbol{A}}\sum_{f\in \boldsymbol{F}}\sum_{t\in \boldsymbol{T}} c_{Ojf}\, y_{jft}\right) \quad (6.16)$$

where, VAT represents taxes levied by the government, c_{LFjf} are the landing fees per airport and aircraft type, and α is a factor representing the non-operational airline costs as a percentage of operating costs.

Finally, government surplus (6.17) is the difference between the aeronautical revenues and taxes and the variable costs of the airport. In this approach it is assumed that local airports are publicly owned. Consequently, the government collects the landing fees, departing passenger taxes, security taxes, and the value added tax (VAT) which is a function of the airfare. The fixed costs of the airport, which are independent of the network design, have not been included in this analysis but could easily be added as a constant to W_G.

$$W_G = \sum_{j\in \boldsymbol{A}}\sum_{f\in \boldsymbol{F}} c_{LF_{jf}} \sum_{l\in \boldsymbol{L_j}} x_{lf} + \sum_{i\in \boldsymbol{I}} r_{C_i} q_i + \sum_{i\in \boldsymbol{I}} c_{PT_j} q_i + \sum_{m\in \boldsymbol{M}} r_m VAT\left(1-e_{d_m} v_m\right)\sum_{i\in \boldsymbol{I_m}} q_i - \sum_{j\in \boldsymbol{A}}\sum_{h\in \boldsymbol{H}} c_{Aj}\, z_{jh} \quad (6.17)$$

where c_{PTj} represents the aeronautical taxes levied by government agencies on airfares at each airport.

The additional public subsidies that are paid to the airlines as a result of the tender process have not been included in this analysis directly; however it is reasonable to assume that the losses of the airline represent a lower bound on the expected subsidy requested during the tender process.

6.3 Case study

The regional Norwegian air transportation system consists of 61 Public Service Obligations (PSO) routes, located mainly in the North part of the country where air transport is the only viable means of public transport during the winter season (WILLIAMS and PAGLIARI, 2004). The Norwegian geography, climate and demography are decisive factors that explain the large number of routes operated in this manner. In 2010, Norway was populated by almost 5 million residents, corresponding to 16 inhabitants per km^2. A detailed analysis of the current Norwegian network configuration is discussed in LIAN (2010).

Norway has 52 commercial airports receiving scheduled services in 2011, 46 of which are publicly owned by Avinor, the 100 percent government owned company created in 2003. These airports served 93.47 percent of all passengers. The Norwegian air transportation network is noticeably centralized around Oslo. Oslo alone accounted for 44.50 percent (21,093,349 passengers) of the domestic and international passengers and 30.47 percent (223,565 air traffic movements) of the commercial flights processed in 2011 in Norway. Of the 46 Avinor owned airports, 29 airports are classified as local airports that mostly, or solely, serve PSO routes. Most local airports consist of a single runway of around 800 meters, as described in Table 6.2, from which only short take-off and landing (STOL) aircraft operate. Examples of aircraft that operate on these runways are presented in LIAN (2010).

61 routes are operated in Norway under PSO regulations with an average hop length slightly below 200 km. Three airlines operate these routes, including Wideroe, a 100

percent owned SAS subsidiary, followed by Danish Air Transportation (DAT) with 8 routes and Lufttransport with 2 routes operated by helicopter. The airfares on the PSO routes are price capped on point-to-point services but not on an itinerary that includes non-PSO segments. According to the available airfare data from OAG for November 2011, non-business passengers pay on average 50 percent of the maximum airfares set by the PSO requirements while business class pay 96 percent of the maximum, giving an overall average of 86 percent.

Table 6.2 - Runway length (in meters) and operational costs per hour (US/hour) for the local airports in Norway

IATA Code	Airport	Runway (m)	Operating Costs (USD/h)	IATA Code	Airport	Runway (m)	Operating Costs (USD/h)
ANX	Andøya	2468	860	NVK	Narvik	799	746
BJF	Båtsfjord	810	431	OSY	Namsos	812	717
BNN	Brønnøysund	1199	1228	RET	Røst	800	628
BVG	Berlevåg	879	654	RRS	Røros	1720	700
FDE	Førde	930	595	RVK	Rørvik	800	691
FRO	Florø	1199	1003	SDN	Sandane	800	650
HAA	Hasvik	859	916	SKN	Stokmarknes	889	947
HFT	Hammerfest	890	1038	SOG	Sogndal	930	955
HOV	Ørsta-Volda	950	755	SOJ	Sørkjosen	859	741
HVG	Honningsvåg	860	705	SSJ	Sandnessjøen	931	779
LKN	Leknes	799	927	SVJ	Svolvær	876	830
MEH	Mehamn	800	602	VAW	Vardø	1085	610
MJF	Mosjøen	889	914	VDB	Fagernes	1989	873
MQN	Mo i Rana	799	851	VDS	Vadsø	870	712

Three major assumptions have been made in our case study in order to restrict the analysis to the regional air transportation system and to present an approach that designs a PSO network.

(1) Only local airports are explicitly analyzed.

We consider the airports that are mainly or only served by PSO routes. Larger regional airports are served mostly by commercial carriers which are beyond the scope of this analysis. We include the regional airports for connecting itineraries but we do not consider the airport revenues and costs in the social welfare analysis.

(2) The case study includes only O/D markets that connect through at least one local airport.

Local airports are mostly served by PSO flights, therefore passengers on markets to/from those airports will be using the PSO system.

(3) Flights connecting two non-local airports are fixed according to the 2010 schedule.

Connecting itineraries may use flights between two non-local airports. In this case we assume that the flights are fixed including both departure and arrival times. Passengers are assigned to these flights although the model does not consider the costs or revenues generated.

Through the case study, three scenarios which consider the optimal fleet mix, airfare variation and the level of service offered to passengers were tested. Each scenario is compared to the 2010 PSO network and the potential solutions are discussed jointly. In the first scenario, given the existing fleet we optimize the PSO route network and search for the optimal fleet configuration. In this scenario, airfares remain at current levels. In the second scenario, airfare variation per market is endogenized, hence demand will fluctuate. Two alternatives are tested: first, airfare variation is unlimited; second, airfares cannot vary by more than 5 percent. In both cases the model also determines the optimal fleet configuration. In the third scenario, we limit the maximum passenger waiting time to the current values and, subsequently, to a maximum 3-hour waiting time between legs of an itinerary.

In the remainder of this section, first is described the data used in the case study and then presented the results for each scenario beginning with an analysis of the current network.

6.3.1 Input Data

The input data was provided by the OAG, EUROCONTROL, official reports published by the Norwegian authorities and the academic literature. Data collected for the case study includes airport operating costs, demand levels per market, flight time per leg, flight costs per leg and aircraft type, off-base costs, airline indirect costs, value of time per passenger type, maximum airfares per market, and the daily demand distribution.

Airport costs for each local airport were divided into fixed and operating costs. The fixed costs are not dependent on the number of hours that the airport is open, therefore are not included in the optimization. The operating costs are directly related to the daily operations of the airports and are derived from official reports. The operating costs per hour per local airport were computed by dividing the total operating costs by the number of hours that the airports were open in 2010 as presented in Table 6.2. We assume that an airport must be open at least one hour before take-off and a half hour after an aircraft landing.

Demand data and flight time per leg were collected from OAG statistics for the 16th November, 2011. The flight time per leg was assumed to be the minimum flight-time according to the OAG statistics (Table 6.3).

Flight costs per block-hour (BH) are the airlines' direct operating costs which include fuel, crew, and maintenance. The block-hour costs were computed using regression analysis for aircraft with less than 100 seats using data drawn from EUROCONTROL (2009). Three aircraft were considered in this case study including 19, 39, and 78-seater aircraft and the cost per block-hour was valued at US 811.9, US 1,503.9 and US 2,853.4, respectively. Currently, the minimum aircraft size permitted is a pressurized 30-seat cabin aircraft, although on certain routes non-pressurized aircraft above 15 seats, such as the 19-seater Dornier 228, have been allowed. The off-base costs were assumed to be 1/3 of the direct operating costs (SWAN and ADLER, 2006).

The value of time per passenger type, an important element in the passenger time cost computation, was estimated by RAMJERDI et al. (1997) for the Institute of Transport Economics. The value of time for different modes of transport and travel purpose was determined as a percentage of the gross average wage in Norway in 1995 (108 NOK/hour). Based on the gross average wage in Norway in 2010 (243 NOK/hour), we determined the value of time for this study: US 54.5 and US 73.2 per hour (equivalent to 300 and 403 NOK/hour) for leisure and business passengers, respectively. Flight time costs and waiting time costs were set equal to the value of time, while schedule delay costs were assumed to be approximately 20 percent and 29.5 percent of that value (US 11.0 and US 43.6 per hour) for leisure and business passengers, respectively, as described in RAMJERDI et al. (1997).

Airfares per market were obtained separately for PSO and non-PSO routes. For PSO routes, the airfares were set at 86 percent of their maximum value, which is the weighted average of the airfares available in the OAG database, divided by business and non-business passengers (Table 6.3). For the non-PSO routes, we conducted a regression analysis, based on OAG data, in order to calculate the average values per market, taking into account the percentage of business and non-business demand.

Table 6.3 - Flight-time (in minutes) and average airfares (USD) for the PSO routes

Route	Flight time (min)	Airfares (USD)	Route	Flight time (min)	Airfares (USD)	Route	Flight time (min)	Airfares (USD)
OSL-FDE	57	255	ALF-HVG	33	151	TOS-ANX	30	107
OSL-FRO	69	255	ALF-KKN	46	170	TOS-HAA	33	164
OSL-HOV	61	255	ALF-MEH	41	175	TOS-LKL	48	182
OSL-RRS	52	278	ALF-VDS	48	170	TOS-SOJ	25	87
OSL-SDN	57	255	BOO-ANX	45	225	BJF-BVG	18	62
OSL-SOG	47	220	BOO-BNN	45	211	BJF-HFT	42	154
OSL-VDB	30	125	BOO-LKN	26	124	BJF-HVG	33	104
BGO-FDE	30	156	BOO-MJF	39	181	BJF-MEH	23	62
BGO-FRO	35	156	BOO-MQN	30	132	BJF-VDS	23	104
BGO-HOV	42	216	BOO-NVK	40	182	BVG-HFT	40	154
BGO-SDN	37	188	BOO-RET	25	124	BVG-HVG	29	122
BGO-SOG	33	156	BOO-SSJ	35	181	BVG-MEH	17	77
TRD-BNN	44	204	BOO-SVJ	27	124	BVG-VDS	26	96
TRD-MJF	51	225	KKN-BJF	27	122	HAA-HFT	20	77
TRD-MQN	64	249	KKN-BVG	32	104	HFT-HVG	25	104
TRD-OSY	30	140	KKN-HFT	47	170	HFT-MEH	35	135
TRD-RVK	34	178	KKN-HVG	41	170	HFT-VDS	44	170
TRD-SSJ	53	225	KKN-MEH	36	146	HVG-MEH	20	77
ALF-BJF	45	175	KKN-VAW	22	81	HVG-VDS	38	154
ALF-BVG	44	170	KKN-VDS	15	62	MEH-VDS	32	128
ALF-HFT	24	77						

Finally, the daily demand distribution was determined separately for domestic business and leisure passengers and international passengers. For leisure passengers we assume a uniform distribution of desirable travel times across the day. For business passengers, we assume that the desirable travel times are equally divided between a 2 hour peak in the morning and evening. The morning peak is between 8 and 10am (arrival time) and the evening interval is 6 and 8pm (departure time). The departure times corresponding to the earliest arrival times were calculated assuming a non-stop flight between the origin and destination. For international passengers, based on the current schedules, we assume the desirable arrival (departure) time to be one hour before (after) the scheduled international flight and exclude connections of less than 30 minutes.

6.3.2 Model Results

In order to analyze the results, we compare the current solution and the optimal solutions for the three scenarios with respect to the following indicators: total, flight, passenger, and airport costs, airfares, fleet requirements, number of flights, flight frequency, cost per available seat-kilometer (CASK), load factor, the total number of passengers, passenger waiting times, and social welfare (passenger, airline, and government). The results are presented in Figure 6.1 and Tables 6.4, 6.5, and 6.6.

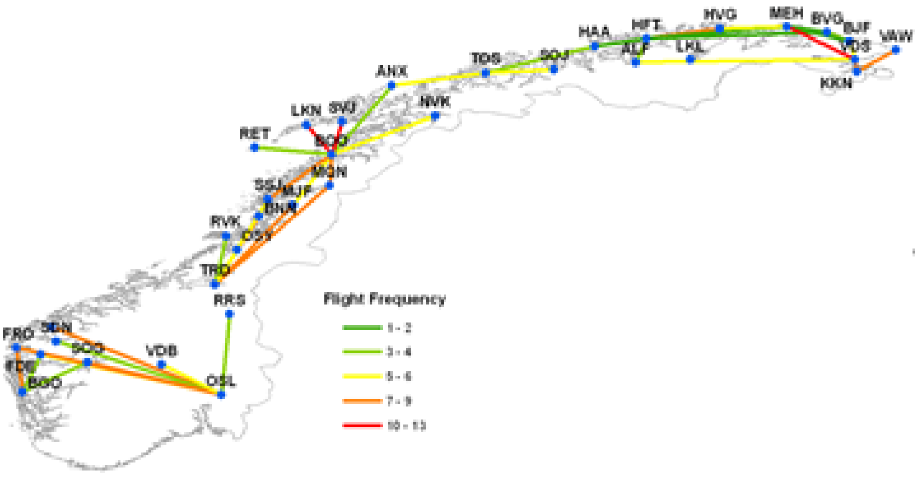

Figure 6.1 - Flight frequency for the Norwegian PSO network

The current network has a daily expected total social cost of US 3.05 million of which US 0.215 million correspond to airline operating costs, US 1.43 million to airport costs, and US 1.19 million to passenger time costs. Airfare revenue on PSO flights amounts to US 0.122 million. The current fleet is composed of three 19-seater, twenty-one 39-seater, and seven 78-seater aircraft. A total of 325 flights achieve an average load-factor of 60.2 percent and the CASK amounts to US 0.129. A total of 6,852 passengers are carried, of which 62 percent travel on non-stop itineraries, 35 percent on 1-stop itineraries, and 3 percent on 2-stop itineraries. Passengers traveling on connecting itineraries have an average waiting time between flights of 163 minutes. Finally, the social welfare analysis computed an average passenger utility of US 237.2 and a total passenger utility of US 1.63 million, a government deficit of US 1.29 million, and an airline deficit of US 0.382 million, which we assume represents a lower bound on subsidies.

Table 6.4 - Optimization model total social costs and airfares for the current network and optimum networks

Model Scenario		Total Cost		Airline Costs		Aiport Costs		Passenger Time Costs		Airfares	
		Value	Var %	Value	Var %	Value	Var %	Value	Var %	Value	Var %
Current Network		3.048	-	0.427	-	1.433	-	1.188	-	0.122	-
Fleet Optimization	Fixed fleet	2.080	-31.8	0.337	-21.2	0.568	-60.4	1.176	-1.0	0.122	-
	Optimum fleet	1.883	-38.2	0.311	-27.1	0.564	-60.6	1.008	-15.1	0.122	-
Airfare Variation	Free variation	1.704	-44.1	0.275	-35.5	0.572	-60.1	0.856	-27.9	0.112	-8.5
	5% variation	1.859	-39.0	0.291	-31.7	0.565	-60.6	1.003	-15.5	0.121	-0.7
Passenger waiting time	Current waiting time	1.758	-42.3	0.284	-33.5	0.569	-60.3	0.905	-23.8	0.119	-2.7
	Maximum 3-hour time	1.773	-41.8	0.314	-26.5	0.568	-60.4	0.892	-24.9	0.121	-1.3

Table 6.5 - Number of flights, average load factor, average waiting time, cost per available seat-kilometer, and fleet for the current network and optimum networks

Model Scenario		Number of Flights		Average Load Factor		Average Waiting Time (min)		Cost Available-Seat KM		Fleet (19/39/78)
		Value	Var (%)	Value	Var (%)	Value	Var (%)	Value	Var (%)	
Current Network		325	-	60.2%		163		0.129		3 / 21 / 7
Fleet Optimization	Fixed fleet	327	0.6	64.8%	7.8	153	-6.3	0.126	-2.0	3 / 21 / 7
	Optimum fleet	341	4.9	79.9%	32.7	121	-25.7	0.105	-18.3	15 / 12 / 5
Airfare Variation	Free variation	303	-6.8	78.6%	30.7	141	-13.4	0.094	-27.2	14 / 8 / 4
	5% variation	313	-3.7	79.1%	31.4	133	-18.3	0.100	-22.5	16 / 7 / 4
Passenger waiting time	Current waiting time	314	-3.4	76.6%	27.3	114	-30.0	0.103	-19.9	16 / 8 / 4
	Maximum 3-hour time	328	0.9	74.6%	23.9	101	-38.0	0.107	-16.6	18 / 8 / 4

Table 6.6 - Social welfare results for the current network and optimum networks

Model Scenario		Government Surplus		Airline Surplus		Passenger Utility			
						Total		Average	
		Value	Var (%)	Value	Var (%)	Value	Var (%)	Value	Var (%)
Current Network		-1.29	-	-0.382	-	1.63	-	237.22	-
Fleet Optimization	Fixed fleet	-0.44	66.1	-0.281	26.5	1.76	8.1	256.43	8.1
	Optimum fleet	-0.44	65.8	-0.249	34.9	2.05	25.9	298.76	25.9
Airfare Variation	Free variation	-0.46	64.6	-0.224	41.4	1.41	-13.3	248.23	4.6
	5% variation	-0.43	66.4	-0.240	37.3	1.93	18.7	288.45	21.6
Passenger waiting time	Current waiting time	-0.44	65.8	-0.234	38.6	1.90	17.1	301.23	27.0
	Maximum 3-hour time	-0.43	66.4	-0.266	30.4	2.33	43.5	354.65	49.5

6.3.2.1. Fleet optimization

The WFSFA model computed the optimal network given the existing fleet constraint and then chose the optimal fleet. In both cases, airfares and demand were fixed and equal to the current values. The main results and comparisons with the current network are displayed in Tables 6.4, 6.5, and 6.6.

For the fixed fleet (Figure 6.2), the expected social costs decrease to US 2.08 million which represents a 31.8 percent reduction in overall costs the largest savings draw from the airport operating costs which were reduced by 60.4 percent (US 0.568 million). Airline costs were reduced by 21 percent (US 0.337 million) due to a slight increase in load factor (to 64.8 percent) and a 2 percent decrease in CASK. Passenger time costs remain almost unchanged with a decrease of 1.0 percent (US 1.18 million) because much larger savings were available from the supply side. The passenger distribution remained almost identical to that of the current network, although the average waiting time decreased by 6.3 percent to 153 minutes due to a better schedule coordination between flight legs.

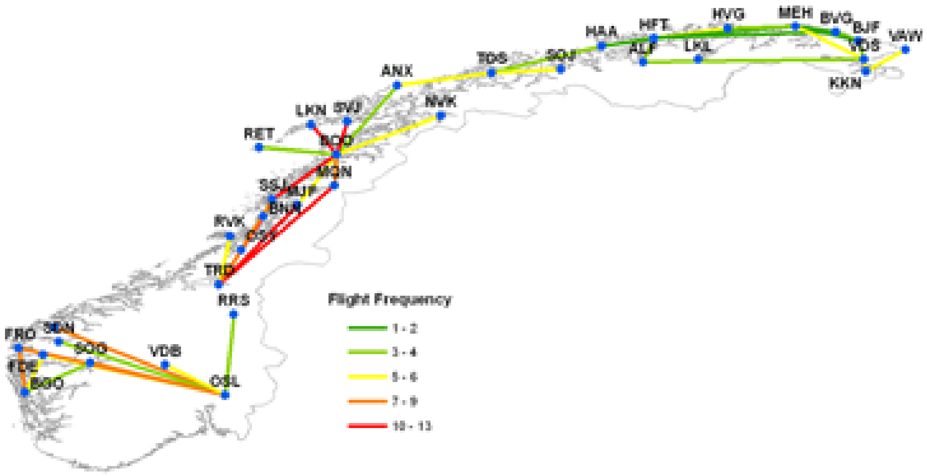

Figure 6.2 - Flight frequency for the optimum fleet network

Thus, the social welfare analysis shows an average and total passenger utility increase of 8.1 percent and the government and airline deficits were reduced by 66.1 and 26.6 percent, respectively. In summation, passenger demand and airfares remain constant, hence the improvement in welfare draws mostly from streamlining the network, slightly increasing the number of non-stop itineraries and reducing waiting times.

When the fleet constraint is removed the total social cost is reduced by 38.2 percent compared to the current network, producing savings of US 1.17 million on a daily basis. The largest reduction draws from the airport operating costs with a 60.6 percent cut, while airline operating costs drop 27.2 percent. The main difference in comparison to the fixed fleet solution is the passenger time cost savings of 15.1 percent instead of 1.0 percent. The fleet merely increases from 31 to 32 aircraft but the fleet composition is substantially different resulting in much lower seat capacity: from 3 to 15 19-seater aircraft, from 21 to 12 39-seater aircraft and from 6 to 5 78-seater aircraft. The optimal fleet mix positively impacts the load factor which rises to 79.9 percent and operating costs which drop by 18.3 percent to US 0.105 million. The increase in load factor, decrease in CASK and increase in flight frequency by 4.9 percent all provide benefits to the passengers. As a result of the higher flight frequency, the average passenger waiting time decreases by 25.7 percent to 121 minutes. The social welfare analysis reflects these improvements with a 26 percent increase in average and total passenger utility and a decrease in airline losses of US 0.249 million, substantially reducing the potential subsidy requests. However, the government surplus is slightly lower than that of the fixed fleet because of the reduction in landing fees, although still 65.8 percent better than the current network equilibria outcome.

6.3.2.2. Airfare Variation

In the airfare variation scenario, we first set an upper bound of 5 percent on any potential changes compared to the current prices and then we remove all constraints.

The main results and comparison with the current network are presented in Tables 6.4, 6.5 and 6.6.

For a maximum airfare variation of 5 percent the total social costs decrease compared to the current network by 39 percent. The total passenger revenues collected on the PSO flights is US 0.112 million which represents an 8.5 percent decrease compared to the current network mainly due to a 2.4 percent reduction in the number of passengers carried and an average 1.8 percent increase in airfares. The airfares increase by 5 percent (the limit) on 38 percent of the PSO routes, airfares increase between 0 and 5 percent on 32 percent of the routes, while the remaining 30 percent of the routes decrease airfares between 0 and 5 percent. The average waiting time is 133 minutes, which is an 18.3 percent decrease compared to the current network. As a result, fewer aircraft are needed (4 less than the current fleet), the number of flights decreased by 3.7 percent, CASK decreased to US 0.1, a 22.5 percent reduction, and the load factor rose to 79.1 percent. The social welfare analysis shows that all stakeholders are better off compared to the current network with increases of 18.7 percent in the total passenger utility, 66.4 percent with respect to government surplus and a 37.3 percent reduction in airline losses.

After removing the 5 percent limitation on airfare variation, the total social costs drop further achieving a 44.1 percent reduction compared to the current network and an 8.4 percent reduction over the 5 percent maximum airfare variation (Figure 6.3). Compared to the 5 percent maximum airfare variation, the greatest change is in passenger time costs whereas airport costs suffer a slight increase. The airfares increase by 10.8 percent which leads to a decrease in demand of 17.2 percent in the total number of passengers whilst maintaining the same relative itinerary choice. Airfare variation was more asymmetric than the previous 5 percent maximum variation scenario, ranging from +41.7 percent (VDS – HFT) to -12.5 percent (OSL – HOV) compared to the current airfares, although 60 percent of the PSO markets show a variation of less than 5 percent (Figure 6.4).

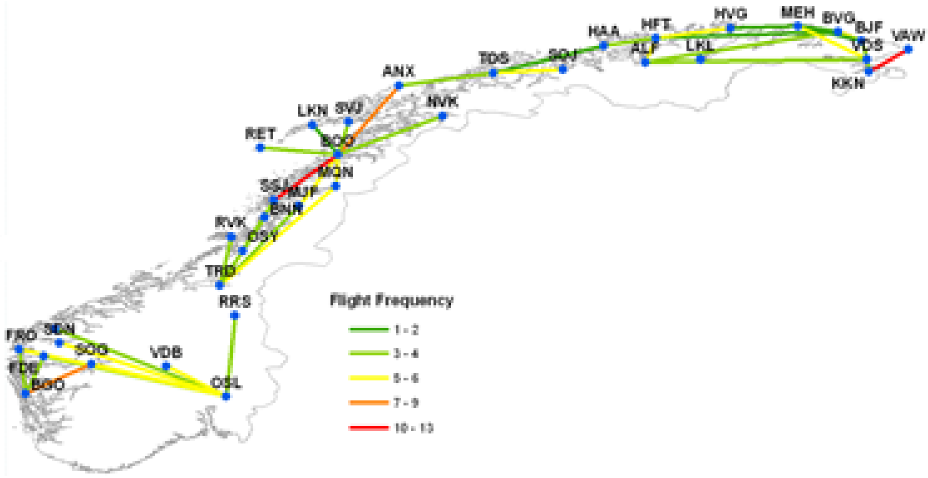

Figure 6.3 - Flight frequency for the optimum network with unlimited airfare variation

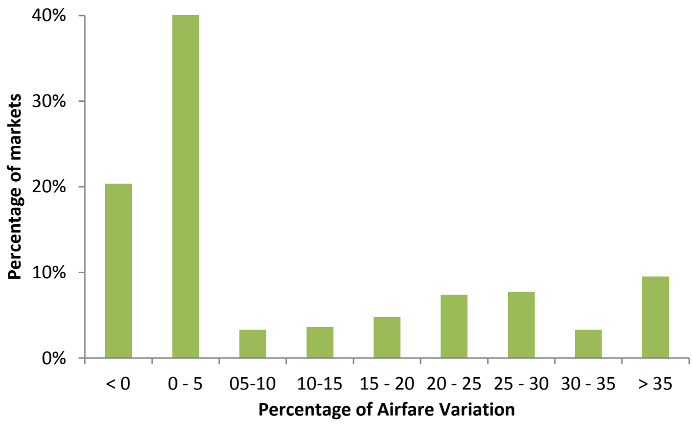

Figure 6.4 - Airfare variation from the current network for the optimum network with unlimited airfare variation

Compared to the 5 percent maximum airfare variation, only the airline surplus has improved because the airport revenues drop due to the decrease in the number of passengers. The average passenger utility increases only 4.6 percent compared to the current network, which is a 17 percent drop compared to the previous result because the number of flights decreases and the average waiting time increases. Moreover, the total passenger utility is lower than the current network by 13.3 percent. In other words, capping the airfares is necessary if the government wants to maintain passenger throughput and airport activity.

6.3.2.3. Passenger waiting time

One of the more complicated issues connected to the design of a subsidized networks is the decision with respect to service levels. Simply defining service levels is a question in its own right as it may be expressed in terms of flight frequency, airfares, or maximum waiting times across all remote areas given budget constraints. In this scenario, we focus on the passenger waiting time by restricting waiting time per market to the current value and then by limiting the waiting time to three hours per stop. The main results and comparison with the current network are presented in Tables 6.4, 6.5 and 6.6.

After restricting waiting time to the current level per market the total social cost drops by 42.3 percent compared to the current network. The largest gains draw from a 33.5 percent reduction in passenger time costs (US 0.904 million). Consequently, social welfare significantly improves for passengers, with an average passenger utility increase of 27.0 percent and a total increase of 17.1 percent despite an average airfare increase of 5.6 percent and a reduction in passengers of 7.8 percent. This result draws entirely from the reduction in average waiting time to 114 minutes which represents a 30.0 percent improvement over the current network. The reduction in the average waiting time is mainly due to a reduction on the longest waiting times in the system. The maximum waiting time is in the market BJF – MOL – LKN with two passengers waiting for 4.5 hours compared to 7.5 hours in the current network. Indeed, in the current network 14 passengers wait for almost 8 hours and 12 percent wait above 4 hours while the maximum waiting time in this scenario is below 5 hours and only 2 percent wait more than 4 hours (Figure 6.5).

Overall, the total revenue collected from airfares drops by 2.7 percent as a result of the decrease in the number of passengers. This decrease is also reflected in a decrease of the number of flights by 3.4 percent compared to the current network and a reduction of 3 aircraft in the total fleet. The social welfare analysis shows that the government and airline are better off than in the current network with 65.8 percent and 38.6 percent gain. In other words, it is possible to increase the level of service to passengers without compromising airline and government surplus.

By limiting the maximum waiting time to 3 hours, the objective is to further increase the level of service to passengers. Overall, the results show further gains for the passengers with the average and total passenger utility rising by 49.5 and 43.5 percent, respectively, as compared to the current network. This gain is derived from a 24.9 percent decrease in passenger time costs and 4 percent decrease un the total number of passengers compared to the current network. Moreover, passenger waiting time drops by 11.4 percent beyond that of the previous case. The average waiting time is 101 minutes with 21 percent of the connecting passenger waiting less than one hour and 82 less than two hours. This is a significant improvement over the current network in which only 70 percent waited less than two hours (Figure 6.5). The cost of this solution is a decrease in government surplus of 13.3 percent compared to the previous case while airline surplus remains almost unchanged. These results reflect the focus on the level of service offered to passengers. In addition, government agencies and airline are still significantly better off as compared to the current network equilibria but not as much as other scenarios (Figure 6.6).

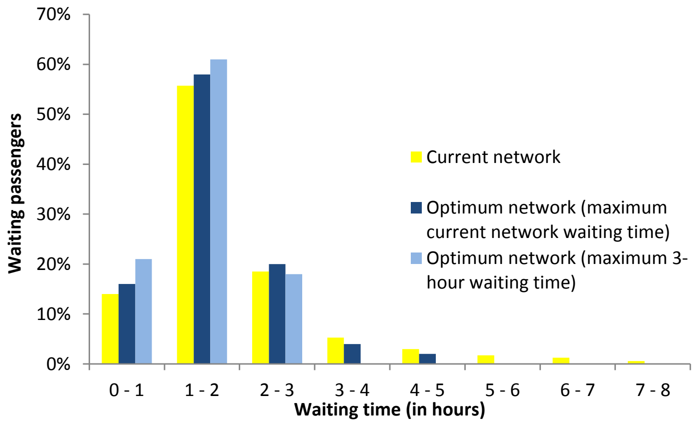

Figure 6.5 - Passenger waiting time for the current and passenger waiting time optimum networks

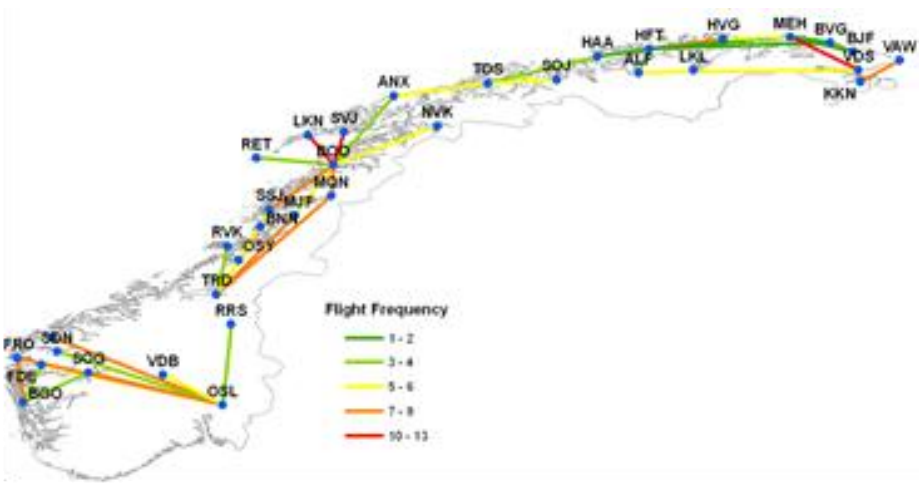

Figure 6.6 - Flight frequency for the optimum network with 3-hour maximum passenger waiting time

6.3.3 Computational Effort

The WFSFA optimization model was solved using the optimizer version 22.01.04 of the commercial software Xpress (FICO, 2011) on a Quad Core processor with 4GB of RAM. The total number of integer variables was approximately 110,000. Before applying the optimizer, a set of preprocessing methods were performed reducing the number of integer variables to around 48,000. The maximum passenger waiting time constraint has a substantial impact on the number of constraints and problem size. For the current network, the computation time required was 3.0 minutes including a LP relaxation of 2.1 seconds. For the optimal solutions, the average computation and LP relaxation times were, respectively, 20.1 hours and 20.6 seconds. The computation time required to reach optimality varied between 7.0 hours and 30.8 hours with the shorter time covering the first scenario and the longer time necessary for the 5 percent airfare variation scenario. The LP relaxation took between 9.2 and 37.3 seconds for the same scenarios.

It is clear that the two sets of integer variables that cover flights and airport operating hours are one of the reasons for the computational complexity and the size of the branch-and-bound tree. Furthermore, the optimum solution balances different and conflicting costs, namely airport, airline and passenger time costs. We also recognize that the computer capacity was not ideal for this size of problem, in particular the RAM capacity. Despite those limitations, the computation time required seems to be reasonable for a strategic approach to be applied on a three to five year basis, In addition, the case study encompasses the largest PSO network currently operated globally.

6.4 Conclusions

This research proposes a welfare based flight schedule and fleet assignment optimization model in order to design a publicly supported air transportation network that balances the social costs of the system across the relevant stakeholders.

An application of the approach to the Norwegian regional network, the largest European public service obligation system, illustrates the trade-offs between potential solutions for a number of scenarios. Perhaps surprisingly, all the results improve the outcome over the current network solution for all stakeholders. In particular, airport operating costs are reduced by more than one half for all alternative scenarios, which clearly indicates the potential to reduce expenditure in the airport system without compromising the level of service offered to passengers. It is also clear that the current fleet composition ought to be altered with greater emphasis placed on the 19-seater aircraft as compared to the 39-seater aircraft, which reduces airline operating costs. Finally, the changes suggested have a relatively small impact on passenger utility unless specific service level targets are defined such as limiting the maximum waiting time. Overall, the network will require subsidies unless airport charges and passenger price caps are increased but on a much smaller scale than necessary today, irrespective of the scenario.

With these findings some general remarks about setting PSO requirements can be made. First, the outcomes indicate that governments in charge of subsidized network should integrate airport and airline operating costs in their analyses. By doing so the public expenditure across the network may decrease. Second, a mathematical model as described in this research could aid government agencies to publish more flexible PSO requirements. The results of the analysis have tightened the airline schedule leading to a network closer to the socially optimal solution. Third, it might be useful for governments to relax some of the aircraft specifications in the PSO requirements as aircraft pre-requisites tend to be too restrictive, increasing the CASK and lowering the load factors without significantly improving the level of service offered to passengers. This could also lead to a more competitive and cost efficient tender process with benefits for both passengers and society.

The social welfare analysis would appear to be a valuable contribution to the air transportation literature analyzing low-demand, subsidized, air transportation networks. However, the current analysis has some limitations and possible improvements that should be point out. The main limitation is that we have considered only one passenger type. Considering business and non-business passengers separately should enhance the accuracy of the model as the behavior of these passengers is different. A second limitation has to do with the passengers' desirable travel times. Our approach is quite simple and based on typical considerations and findings from existing literature. Specific analysis for this type of network may improve the daily demand distribution, hence the results of the modeling approach. Finally, in terms of computational effort, we believe we have reached the maximum network size that can be solved with exact methods. Specialized algorithms may be needed if we want to improve and/or add new elements to the model formulation.

Chapter 7

Conclusion

This doctoral thesis addresses a number of problems involved in the design of congested and low-demand, subsidized aviation networks through a set of optimization models. The network design optimization models determine optimal flight schedule and fleet assignment decisions for aviation networks using different objectives and perspectives. These decisions are relevant for: airlines in their planning process; for transport authorities in their strategic decision regarding a more reliable and sustainable air transportation system; and for governments in their regulatory role.

The thesis pursued two global objectives, set in the Introduction, one for congested networks and the other for low-demand networks. Both global objectives were fully accomplished through the five network design optimization models developed: three focusing on congested networks and two on low-demand networks. Models relating to congested networks deal with different problems faced by airlines, aviation authorities, and governments. The specific objectives set for congested aviation networks are satisfied throughout Chapters 2, 3, and 4

Chapter 2 presents a network design model to determine the optimal slot allocation decisions for a publicly owned network. The main contribution of this chapter is the definition of optimal slot allocation decisions so that the total social costs of the network are minimized, while satisfying a given leg-based demand with a given fleet. This approach is suited for governments or aviation authorities in charge of air transportation networks. Another contribution of this chapter is the consideration of delay costs for aircrafts and passengers in the network's total costs. The results from an application to the main network of Portuguese airports show a decrease in the network costs, increasing the number of passengers and flights. Indeed, the network costs drop 13.0 percent to 1.533 million EUR/day while the number of daily passengers increases from 7982 to 8524 (+ 6.8 percent).

Chapter 3 introduces a network-wide approach to analyze whether the existing airport capacity and slot distribution are capable to accommodate the expected passenger demand with lower costs, including delay costs. To the best of my knowledge, this is the first model of this kind developed and applied to slot-constrained airport networks. The approach is based on an optimization model that minimizes the total costs of a liberalized, slot-constrained and congested aviation network. It takes into account airline market power, number of slots per airport, available fleet, and expected airport delay time. The model can be used by aviation authorities to test and propose different slot configurations (or demand management measures), enhancing the information available to authorities in charge of those decisions. The approach applied to the 10-largest airports and 8 airlines in Europe led to a significant reduction in the total network cost mainly by cutting by more than half the expected delay costs. With respect to the actual network, the total network costs decrease 10.4 percent to 39.12 million EUR/day, while the delay costs drop by 56.4 percent to 1.18 million EUR/day. All airlines in the application reduce their costs from the actual network between 6.9 and 14.3 percent, while the costs also drop for all airports, in this case between 6.8 and 15.4 percent.

Chapter 4 describes an integrated flight schedule and fleet assignment model for airlines operating in congested, competitive and slot-constrained networks. In this model, demand is considered by O/D market which is an important improvement with respect to Chapters 2 and 3. The main contribution of this chapter to the existing literature is the consideration of delay costs in the airline scheduling process, using the expected airport delay time to obtain the expected delay costs for both aircraft and passengers. Other improvement to the existing literature is the consideration of airline competition effects, assuming that competitors' frequency is known. Airline market share is then determined as function of the airline frequency through the model. The model was applied to the TAP Portugal main network, which involves 31 airports. The results indicate a possible increase of airline profits by 5.2 percent, corresponding to 25,092 USD/week. The gains in profit are achieved mostly by reducing delay costs to 8.4 percent of total costs, instead of 9.8 percent for the actual network. This reduction is attained decreasing by 2.2 percent the number of flights and increasing by 8.0 percent (7 minutes) the passenger average connecting time.

Chapters 5 and 6 focus on low-demand, subsidized aviation networks. To the best of my knowledge, network design models had never addressed specifically this type of networks. However, as accountability for the use of public funds increases, it becomes more important to determine whether essential aviation services can be set in such a way that public expenditure is reduced and passenger level of service is enhanced.

Chapter 5 presents an integrated flight schedule and fleet assignment model which is to the best of my knowledge the first model of this kind developed for subsidized air transportation networks. Another contribution to the existing literature is the decision approach set for determining the airfares per market and, consequently, the expected public subsidies using the outputs of the optimization model. This approach assumes a target number of O/D passengers to satisfy. The decision approach was applied to the Azorean network, which comprises 9 airports. The results show reductions of airline costs and passenger time costs of, respectively, 14.9 percent and 1.3 percent. With those cost savings, the average airfares and the expected public subsidies also decrease by 8.3 and 6.7 percent, respectively. These results are obtained with two less flights than in the actual network (40 instead of 42) and using only five aircraft, instead of the six needed to run the actual network.

Chapter 6 presents an optimization model with important additional features with respect to the model of Chapter 5, and a detailed social welfare analysis of the results. The new model includes airport costs and passenger schedule delay costs in the network costs, which did not happen in the previous model. Also, airfares are decided during the optimization phase and not after, like in Chapter 5. A significant contribution to the existing literature is the utilization of the outputs of the optimization model in the analysis of welfare implications for all the players in the system: passengers, airlines, airports, and governments. The model and subsequent welfare analysis were applied to the Norwegian regional network, which involves 29 airports. Comparing to the actual network, the results obtained signify a reduction of total costs between 31.8 and 44.1 percent. Most of the cost reduction is due to decreases in airport operating costs between 60.1 and 60.4 percent. The most significant welfare gains are for the government, whose welfare increases by more than 64 percent for all model scenarios.

The results obtained in the applications show the usefulness of the various optimization models. Despite this, it is important to underline some overall findings due to their importance for congested and low-demand networks. First, the use of airport capacity in congested networks may be enhanced without compromising airline and passengers' objectives by adapting airline schedules. Second, it seems that airlines operating in congested networks will benefit from incorporating delay considerations since the beginning of their schedule design process. Third, it appears that governments in charge of subsidized networks might reduce public expenditure with the aviation network (airlines and/or airports) and still increase the passenger level of service. Also it appears that this type of networks really needs to simultaneously consider airline, passenger, and airport costs to improve the overall network design and social welfare.

Despite the effort made to build real-world case studies, it should be emphasize that the case studies are hypothetical. Indeed, some assumptions were made due to lack of data or to restrain the analysis to the thesis objectives. Nevertheless, the usefulness of the optimization models and decision tools described in this thesis is demonstrated by the results and the models can be used in practice as they are or with minor adjustments.

Improvements and future research work identified in Chapters 2 to 6 can enhance the accuracy of the models. Despite this, the author believes that the models introduced and applied in this thesis represent a valuable contribution for the existing knowledge about aviation network design, especially for congested and low-demand networks. The case studies, largely based on real-world networks, clearly exemplify this contribution for airlines, aviation authorities, and governments in their network design decision process.

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